

Information Systems for Child Nutrition in Zimbabwe

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Abstract

This work examines patterns of under-nutrition prevalence, based on data gathered through a growth monitoring programme run as part of a health information system by the Zimbabwean government. Most of the thesis makes use of secondary data – collected by other investigators for different purposes – but use is also made of a questionnaire survey of households in the Buhera district of Zimbabwe. Patterns of attendance and bias are assessed initially through a comparison of health information system statistics with census results and an independent, community-based anthropometric survey. Attendance is found to vary both across districts and over time, raising doubts about the validity of analysing trends in under-nutrition in the growth monitoring data. However, it is found that provincial estimates of underweight prevalence in the government's information system and the independent survey are well correlated, suggesting geographical comparisons are possible. Overall, the information system slightly under-estimates underweight prevalence nationally in comparison with the independent survey.

Under-nutrition prevalence data from the growth monitoring scheme are examined using regression analysis to identify temporal and spatial patterns. The pre-harvest period between January and March is found to be the season when underweight prevalence is greatest. Levels of under-nutrition are also found to have declined during the information system's life-time, though this apparent trend may be related to changing patterns of attendance. Agricultural, meteorological, infra-structural, and socio-economic data are collated within a Geographic Information System and related to the observed patterns of under-nutrition prevalence. Spatially, the areas which suffer from persistent problems of under-nutrition are those where rural poverty is greatest. Yearly fluctuations in district-level under-nutrition are found to be related to changes in rainfall, whilst monthly fluctuations are correlated with reported diarrhoea cases among children.

A spatial simulation model of growth monitoring attendance is constructed for Buhera district, using the household survey data. The model's performance is poor when compared to health facility statistics, but the methodology developed enables data from different sources and different scales to be integrated. It is concluded that the methodology developed for analysing growth monitoring data in the thesis may have application elsewhere in southern Africa.

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Note concerning publication of thesis material

The following published papers were based on work presented in this thesis:

Wright, J.A., Gundry, SW, Ferro-Luzzi A, Hoyles PJ, Vaze, PB, Nyatsanza J & Dent JB (*in press*): 'Identifying temporal and spatial trends in growth monitoring data and the links to socio-economic and environmental variability in Zimbabwe'. *Ecology of Food and Nutrition*. © OPA (Overseas Publishers Association), Amsterdam, BV.

Wright, J.A., Gundry, S.W., Ferro-Luzzi, A. and Hoyles, P.J. (1997): 'Validation of a Complex Spatial Model of the Food and Nutrition System in Zimbabwe'. Proceedings, *ModSim 97, the International Congress on Modelling and Simulation*, Hobart, Tasmania. 8-11 December, 3: 1057-1062.

Copies of these papers, which form part of Chapters 5 and 7 respectively, are given in Appendix 7. I would like to thank my co-authors, SW Gundry, PJ Hoyles, PB Vaze, Prof JB Dent, Mrs J Nyatsanza, and Prof. A Ferro-Luzzi for permission to include copies of these papers.

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Wright, J. A., Gundry, S., Hoyles, P., Nyatsanza, J., and Vaze, P. (1997): 'Seasonal aspects of under-nutrition in young children in Zimbabwe'. Paper presented to the *Development Studies Association Conference*, University of East Anglia, 11-13 September

Wright, J., Hoyles, P.J., Makombe, G., Gundry, S.W., Mudimu, G. and Nyatsanza, J. (1996): 'The Use of Geographical Information Systems for Household Survey Sample Stratification: an Application from Zimbabwe in Nutrition and Food Systems Research'. Paper presented at the *Development Studies Association Conference*, University of Reading, 18-20th September

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List of Abbreviations Used

ARI – Acute Respiratory Infection, meaning short-term infections of the lung characterised by coughing or difficulty in breathing.

CCD – Cold Cloud Duration, a measure of rain-bearing cloud cover derived from meteorological satellites and used in the interpolation of surface rainfall measurements.

CSO – Central Statistical Office, the Zimbabwean government department responsible for collating statistics.

DCW – Digital Chart of the World, a collection of seventeen different digital map layers originally produced by the U.S. Department of Defense.

DHS – Demographic and Health Survey, a sample survey financed by the U.S. Agency for International Development that took place in Zimbabwe in 1988 and 1994.

DSW – Department of Social Welfare, the Zimbabwean government department responsible for administering drought relief, pensions, and other forms of welfare.

DTM – Digital Terrain Model, a computerised representation of the shape of the Earth's surface.

ESAP – Economic and Structural Adjustment Programme, a package of policy reforms implemented by the Zimbabwean government since 1991.

FAO – the Food and Agriculture Organisation of the United Nations.

FEWS – Famine Early Warning System, a project funded by the U.S. Agency for International Development that attempts to warn the international community of impending food shortages within the developing world.

GIS – Geographical Information System, used for the input, storage, manipulation, analysis and output of digital maps and associated information.

GMB – Grain Marketing Board, a parastatal or quasi-governmental organisation that formerly controlled strategic grain reserves, grain movements, and prices.

GPS – Global Positioning System, a system of satellites and receivers that can be used to locate features on the Earth's surface with a high degree of accuracy.

LSCFA – Large Scale Commercial Farming Areas, agricultural land characterised by large holding size, high potential, and large numbers of farm workers. This land formerly

comprised Rhodesia's European Areas and remains predominantly owned by white Zimbabweans.

MUAC – Mid-Upper Arm Circumference, an anthropometric measure used to assess nutritional status in both adults and children.

NCHS – National Centre for Health Statistics, an organisation involved in the definition of standards.

NDVI – Normalised Difference Vegetation Index, a measure of the 'greenness' of vegetation derived from satellite imagery. NDVI is based on the change in the reflectance characteristics of a given area and can be calculated from band data using the formula (near infra-red - red)/(near infra-red + red).

NGO – Non-Governmental Organisation. Examples of such organisations would include the Save the Children Fund, Care International, and the Food and Agriculture Organisation of the United Nations.

NHIS – National Health Information System, run by the Zimbabwean Ministry of Health.

SSCFA – Small Scale Commercial Farming Areas, agricultural land characterised by high potential, small holding size, and commercial production systems. This land formerly comprised Rhodesia's Purchase Areas and remains predominantly owned by indigenous Zimbabweans.

SADC – the Southern African Development Community, a regional grouping of countries extending from Tanzania to South Africa and including Zimbabwe.

UDI – Unilateral Declaration of Independence, the period between 1965 and 1979 when Rhodesia was run by a white minority government under Ian Smith.

VIDCO – Village Development Committee, the lowest tier of government within Zimbabwe's communal lands. The VIDCO is both a political body and a geographical entity comprising around one thousand people.

WHO – World Health Organisation.

ZINATHA – Zimbabwe National Traditional Healers Association, the official body of the country's traditional healers and spirit mediums.

Glossary and Translations of Shona or Zimbabwean words

Anthropometry – ‘The study and technique of taking body measurements, especially for use on a comparison or classification basis.’ (Bender, 1998)

Autocorrelation – ‘statistical concept expressing the degree to which the value of an attribute at spatially adjacent points varies with the distance separating the points’ (Burrough, 1986: p. 177). Can also refer to the degree to which the value of an attribute at adjacent points in time varies over different lags.

Bias – ‘A consistent, repeated difference of the sample from the population, in the same direction; sample values that do not center on the population values but are always off in one direction.’ (Bender, 1998)

Coping strategy – a response to conditions of food insecurity, such as the sale of livestock, the harvesting of wild foods, or the borrowing of grain and money.

Cross-correlation – A correlation between two time series. The observations of one series are correlated with the observations of another series at various lags and leads (SPSS Inc, 1993).

Dambo – an area of wetter drainage, often artificially created by damming a water-course for the purposes of grazing cattle (Shona).

Digitising – the encoding of map co-ordinates in a digital form (Burrough, 1986: p. 179).

Drought relief – government assistance provided to poorer households during times of drought, in the form grain and/or agricultural inputs.

Dummy variable – a variable used in a regression equation taking one of two values (usually zero or one).

Durban-Watson statistic – A test statistic which tests the null hypothesis that the residuals from a regression are independent, against the alternative that the residuals follow a first-order auto-regressive process (SPSS Inc, 1993).

Early warning systems – ‘systems of data collection established to monitor a population’s access to food in order to provide timely warning of impending crises and to elicit the appropriate response’ (Maxwell and Frankenberger, 1992: p. 116).

Exchange entitlement – ‘the set of all the alternative bundles of commodities that he (i.e. a person) can acquire in exchange for what he owns’ (Sen, 1982: p. 3).

Food balance sheets – ‘the principle tools used for calculating national food security...used to determine the expected food deficits or surpluses (Maxwell and Frankenburger, 1992: p. 87).

Food security – ‘Access by all people at all times to enough food for an active healthy life.’ (Reutlinger and Selowsky, 1976).

Geo-coding – ‘The activity of defining the position of geographical objects relative to a standard reference grid’ (Burrough, 1986: p. 179).

Growth monitoring – ‘The practice of following changes in a child’s physical development, by regular measurement of weight and sometimes of length.’ (Bender, 1998)

Height-for-age – ‘An index of past or chronic nutritional status; an index which assesses the prevalence of stunting.’ (Bender, 1998)

Household – ‘One person who lives alone or a group of persons, related or unrelated, who share food or make common provisions for food and possibly other essentials for living’ (FAO, 1990); ‘the smallest and most common unit of production, consumption and organization in societies’ (McLean, 1987)

Kraal – Zimbabwean word for a village or small rural settlement

Kriging – ‘Name (after DG Krige) for an interpolation technique using information about the stochastic aspects of spatial variation’ (Burrough, 1986: p. 180).

Lobolla –the practice of a prospective husband paying the family of his bride an agreed number of cattle in exchange for permission to marry (Shona).

Malnutrition – ‘A nutritional disorder or condition resulting from faulty or inadequate nutrition’ (Bender, 1998)

Mhunga –pearl millet (Shona)

N’hanga – a traditional healer, using techniques such as herbalism to cure the sick (Shona).

Partial autocorrelation – the correlation between values of a series at different times after the effects of the intervening times have been removed (SPSS Inc, 1993).

Precision – ‘degree of accuracy; generally refers to the number of significant digits of information to the right of the decimal point’ (Burrough, 1986: p. 182)

Prevalence – ‘The proportion of the population that has a condition of interest (i.e. wasting) at a specific point in time; a measure of a condition that is independent of the size of the population; a value that is always between 0 and 1.’ (Bender, 1998)

Primary data – data collected specifically for a given purpose and analysed by the same individual or organisation that undertook the data collection

Principal Components Analysis – a technique used to form uncorrelated linear combinations of a given set of variables, commonly used to reduce large data sets.

Rapoko – finger millet (Shona)

Sadza - a porridge, usually made from maize meal, that forms the staple of the Zimbabwean diet (Shona).

Scotch cart – a two or four-wheeled wagon, often pulled by donkeys and used for transporting goods in rural areas.

Secondary data – data collected by one organisation or individual for one purpose, but used by another organisation or individual for another purpose (Frankfort-Nachmias and Nachmias, 1992: p. 291)

Underweight – ‘A condition measured by weight-for-age; a condition that can also act as a composite measure of stunting and wasting.’ (Bender, 1998)

Vulnerability mapping – the identification of the geographical distribution of groups vulnerable to food insecurity.

Weight-for-age – ‘An index of acute malnutrition; a valuable index for use with very young children or when length measurements are difficult to do accurately.’ (Bender, 1998)

Weight-for-height – ‘An index of current nutritional status.’ (Bender, 1998)

Z-score – ‘A statistical measure of the distance, in standard deviations, of a value from the mean; the standardized value for an item based on the mean and standard deviation of a data set; a standardized value computed by subtracting the mean from the data value x and then dividing the results by the standard deviation’. (Bender, 1998)

1. INTRODUCTION

This thesis investigates the use of information systems in alleviating child under-nutrition. UNICEF (1998) estimate that 226 million children worldwide are stunted for their age as a result of malnutrition, mostly in Africa, Asia, and Latin America. The scale of the problem is immense, but information systems can provide support to decision-makers. For example, information systems may identify areas containing a high proportion of undernourished children or changes in malnutrition levels over time. Such information may be used to target resources at specific areas, or to evaluate the impact of policy on nutrition. This study examines the role of information systems in Zimbabwe, where 21% of children under 5 years are considered chronically undernourished (Macro International, 1995: p. 24).

The work presented here can be examined from three different perspectives:

- The first perspective concerns research methodology and the relationship between a researcher and the information (s)he analyses.
- The second perspective concerns information systems, their functioning, and their design.
- The third perspective relates to human nutritional status and its nature and causes at the population level.

Perspective 1:

At the most general level, the thesis examines the consequences of working with secondary data. Secondary data in this context means information gathered by one party for a specific purpose, but analysed by a second party for a different purpose. It is argued that as computing and telecommunications technology become more powerful, this type of data will be increasingly used. This general dimension to the thesis is discussed in greater depth in section 1.1.1 below.

Perspective 2:

At a more specific level, the thesis also examines the way in which an information system operates. The first issue addressed at this level is the extent to which the information collected for the system is capable of supporting the types of analysis intended for it. The thesis also explores some other potential analyses of the data, not currently implemented in the information system at present. The working of the information system is described in Sections 1.1.2 to 1.1.4 below.

Perspective 3:

Finally, in the third perspective, the thesis looks at prevalence patterns of nutritional status. It considers the patterns of under-nutrition among children through time and by area and how these relate to other population characteristics.

The chapter starts with the first perspective, by considering differences between primary and secondary data. It then describes the more specific issues surrounding nutritional information systems and the operation of one such system in Zimbabwe. The causes of child under-nutrition are then discussed, again with reference to Zimbabwe. Existing techniques for analysing secondary nutritional or food security-related information are then reviewed. Finally, some hypotheses concerning all three perspectives (secondary data, information systems, and child nutrition) are then described.

1.1 NUTRITIONAL MONITORING SYSTEMS & SECONDARY DATA

1.1.1 Secondary data versus primary data

Secondary data are defined as data collected by one organisation or individual for one purpose, but used by another organisation or individual for another purpose (Frankfort-Nachmias and Nachmias, 1992: p. 291). This contrasts with primary data, which are collected for a particular purpose and analysed by the same individual or organisation that undertook the data collection. The importance of first-hand observation and experience in many qualitative disciplines means that in practice, there is little secondary use of qualitative data such as interview transcripts or anthropological records. Most secondary data therefore tend to be quantitative. Secondary data form the focus of this thesis, because their importance and use has been increasing over the past ten years. This is partly because the advent of the Internet and the World Wide Web make it much easier for organisations and individuals to distribute information to other researchers. Their increasing importance is, however, also due to the availability of greater computing power and hardware and software for data storage. Improvements in computerised storage media, wider use of computers, and improved technology for data dissemination now mean that detailed data can be stored digitally, instead of printed out as summary tables and stored in paper format. One consequence of this greater use of secondary data is an increasing division of labour within

the research community. This means that some researchers now concentrate exclusively on data storage and management, others solely on data analysis, and others on data collection.

In principle, there are several advantages to analysing secondary data rather than collecting new data. Firstly, from the point of view of efficiency, it clearly makes more sense to make use of information that already exists than to go out into the field to spend time and money making fresh measurements or observations. Digital data can be obtained on CD-ROM by post or increasingly, accessed over the web. In the latter case, the capacity of the web to act as an inventory of existing data is important. The easier it is to find data on the web, the more successful its role will be in this regard. Secondly, greater access to secondary data over the web increases the potential for comparative studies to be made. This is particularly important where patterns of change over time are being examined. Published secondary data can provide a base-line against which subsequent measurements can be compared and changes assessed. It also provides an opportunity to corroborate findings in data sets from different sources. The importance of the web for integrating data from different countries has also often been stressed, although language differences are still a problem. For larger research projects, selling on information can also provide a means of recouping the costs of expensive data collection exercises. Secondary data often also have the advantage of greater coverage so that:

‘with secondary data we can increase the sample size, its representativeness, and the number of observations could lead to more encompassing generalisations’ (Frankfort-Nachmias and Nachmias, 1992).

Finally, there is also a case from a transparency point of view for publishing source data that are analysed and reported in scientific journals. The fact that the original data are available for inspection and re-analysis by other researchers potentially enables published findings to be verified.

Within the context of nutrition and food security, considerable attention and resources have been devoted to strengthening secondary data analysis and information systems. The Food and Agriculture Organisation of the United Nations (FAO) has developed a Global Information Early Warning System to forecast periods of food shortage and therefore demand for food aid (FAO, 1992). Much of the investment in such early warning systems has been in remote sensing and meteorology. For example, recent work has used sea-surface temperatures derived from satellites to predict maize yields in Zimbabwe (Cane *et al.*, 1994). At the same time, the U.S. Agency for International Development (USAID) has funded the strengthening of African data collection networks in collaboration

with the U.S. Geological Survey (USGS). The USGS has acted as a data manager, maintaining the secondary data sets collated in the field in a usable format. Within Zimbabwe itself, the 1992 demographic census received support from the Swedish International Development Agency (Government of Zimbabwe, 1994e). Further investment made in secondary data analysis is described in section 1.3. This raises the question of whether such heavy investment has been worthwhile.

Despite the apparent advantages described above, analyses of secondary data have attracted criticism. Perhaps the most obvious difficulty in trying to interpret information at second hand is the loss of context. Without being involved in the data collection process itself, it can be difficult to understand the background to a survey or map. There is much knowledge and information gained during fieldwork that is inherently difficult to store in a computerised format. In addition, re-use of data places a burden both on the data provider and the data user. The data provider has to spend time documenting all the decisions that were made in gathering information, and the data user has to spend time reading and understanding the background documents provided. In many cases, secondary data also only approximate the kind of data that the investigator would like to have for analysis. In addition, Reynolds *et al.* (1997) has also argued that data providers often receive little credit for their contribution to publications. Furthermore, whilst much information is available over the World Wide Web for Africa (see Chapter 2), relatively few African researchers have the means of accessing this information. This technology is thus likely to benefit international researchers and NGOs and put in-country interest groups and government at a disadvantage. Access to information over the web by the communities that the data relate to is even more limited and this also raises the question as to whether the information has been expropriated. A more participatory means of data storage and analysis would seem preferable to this system.

Secondary data have also attracted more specific criticism within the context of nutrition and food security. Seaman *et al.* (1993) have argued that conventional data collection systems break down during times of severe crop failure and political disturbance. This is demonstrated by Uvin (1994), who has shown that United Nations demographic data for Rwanda do not reflect the atrocities committed in 1991-92 and therefore 'bear little resemblance to the real world' (p. 496). Given that war, rather than the environment, is now regarded as the major cause of famine world-wide, they suggest that the role of secondary data in food security and nutrition will in future be limited. They argue further that

governmental administrative units are not appropriate to the study of populations prone to malnutrition, given that groups with similar livelihoods may be split across several administrative districts and may seasonally migrate between them.

In addition, although some secondary data sets are now available in a highly disaggregated form, it may not be possible easily to replicate analyses performed on more aggregate data. For example, some secondary data in Zimbabwe (e.g. data concerning crop production and household income and expenditure) are based on sample surveys, but sample sizes that are adequate for making inter-provincial comparisons may be inadequate for making inter-district comparisons. Frankenburger and Coyle (1993) have argued that average or aggregate statistics for large populations may not reflect conditions in the poorest sections of society, who are most likely to be undernourished. This problem is exacerbated by the skewed distribution of wealth in many southern African populations and the Zimbabwean Communal Areas in particular (Jackson and Collier, 1988), which means that average statistics can be heavily influenced by data for small, very wealthy minorities. Moreover, Frankenburger and Coyle (1993) have also argued that secondary data are seldom published in a cross-tabulated format, which makes the identification of combinatorial effects (such as the interaction of poor housing and lack of healthcare) more difficult. To some extent, this problem is offset by the fact that many secondary data sets are now being published in an increasingly disaggregated format, making such cross-tabulations easier.

Others have suggested that secondary data fail to capture the true causes of under-nutrition by concentrating on quantifiable factors such as food production at the expense of less measurable social factors. Existing secondary data sets do not generally cover the underlying processes of impoverishment and asset recovery, the 'coping strategies' and decisions made by households in times of stress (Frankenburger and Coyle, 1993), processes of intra-household food allocation, or the livelihoods of different population groups (Seaman *et al.*, 1993; Holt and Lawrence, 1993). In practice, access to secondary data for nutritional forecasting is also constrained by the reluctance of collection agencies to part with sensitive or valuable information for no immediate benefit (Davies *et al.*, 1991) and by problems of confidentiality in releasing disaggregated data.

Finally, it might also be argued that analyses of secondary data and primary data are often carried out independently. Although secondary data might be used to describe trends at the outset of a study based on primary data (for example, rainfall data are used for this

purpose in IIED/FSRU, 1994), the two types of information are seldom closely integrated. An integrated analysis of the two types of data would enable cross-checking of results from both sources and increase the degree of confidence in the conclusions drawn from such a study.

1.1.2 African nutritional monitoring systems

Most nutritional information systems throughout the world make use of anthropometry to assess nutritional status. This involves measurement of an individual's stature and physical condition as an indicator of their nutritional status. Many anthropometric indicators are based on weight and height. In adults, Body Mass Index (weight in kilograms divided by the square of height in metres) is used as an index of nutritional status (Shetty and James, 1988). In children, indicators reflect the change in body size with age. Height-for-age (the height of an individual relative to a typical group of children the same age) is a slowly changing index that reflects stunting or chronic (long-term) under-nutrition. Weight-for-height is a more rapidly changing index that reflects wasting or acute (short-term) under-nutrition (Beaton *et al.*, 1990: p. 8). The third commonly used measure, weight-for-age, can be thought of as combining aspects of both weight-for-height and height-for-age. The process of taking repeated anthropometric measures of children is referred to as growth monitoring. Other anthropometric measurements are based on specific parts of the body. Mid-Upper Arm Circumference, for example, is a commonly used index in both adults and children. In the case of many of these measures, the indices can be expressed in relation to a reference population of healthy individuals. Height or weight measurements for an individual can be expressed in terms of the extent to which they differ from the mean value for healthy individuals of the same age in the reference population. Often, this difference is expressed in terms of reference population standard deviations or Z-scores, in terms of reference population percentiles, or in terms of the reference population median.

Following the promotion of growth monitoring by UNICEF, many Southern African Development Community (SADC) countries have instigated information systems that make use of child anthropometry. As well as the Zimbabwean system that forms the focus of this study, numerous other similar systems exist across the region. Quinn and Kennedy (1994) have documented the data collected under the various national nutritional surveillance programmes in 19 African countries. Their findings are summarised in Table 1.1. Five

other sub-Saharan African countries regularly collect clinic-based weight-for-age data similar to Zimbabwe, whilst Zambia collects Mid-Upper Arm Circumference (MUAC) measurements. Work by other authors suggests that Table 1.1 is incomplete. Serdula *et al.* (1987), for example, describe a surveillance system identical to the Zimbabwean one in Swaziland, yet this does not feature in Table 1.1. All the countries considered collected at least as many indicators as are available in Zimbabwe with the exceptions of Zambia and Tanzania. The variety of indicators collected by different countries reflects the fact that:

'there is still no agreement among donors, governments, and relief agencies as to which indicators to monitor, let alone any consensus on critical points' (Kelly, 1992: p. 444).

Similarly, the Demographic and Health Surveys used in Chapter 3 are also available for virtually all the other SADC countries (Macro International, 1995). The availability of both regular, nationally collected anthropometric data and nutritional indicators in at least six other countries suggest that a methodology developed for Zimbabwe might be transferable to these other areas.

Country	Responsible Organisation	Anthropometric Data	Collating Organisation	Nutritional Indicators
Angola	(none)	(none)	NEWS	1-7
Botswana	NNSS	2	NEWS	1-7
Burkina	FEWS	?	FEWS	1-7, 10
Chad	FEWS	?	FEWS	1-7, 10
Ethiopia	NNSS; FEWS	1	FEWS	1-8, 10
Kenya	NNSS; CHNIS	1, 2	NEWS	1-8
Lesotho	NFNIS	1, 2	NEWS	1-7
Malawi	NSS	1, 2	NEWS	1-8
Mauritania	FEWS	?	SAP	1-7, 10
Mozambique	NSS	1, 2	FEWS	1-7
Namibia	(none)	(none)	NEWS	1-7
Niger	(none)	(none)	NEWS	1-8, 10
Mali	FEWS	?	SAP	1-7, 10
Sudan	FEWS	? (Darfur Province: 1)	FEWS	1-7
Swaziland	(none)	(none)	NEWS	1-7
Tanzania	NNSS	1	NEWS	1-5, 7
Zambia	NNSS	2	NEWS	1-5, 7
Zimbabwe	NSS	1, 2	NEWS	1-7

Table 1.1: *Areas of Data Collection Under African Nutritional Surveillance Programmes*

(adapted from Quinn and Kennedy, 1994. Organisation acronyms are: NNSS - National Nutrition Surveillance System; FEWS - Famine Early Warning System; NSS - Nutrition Surveillance System; SAP - Systeme d'Alerte Precore; NFNIS - National Food & Nutrition Information System; CHNIS - Child Health & Nutrition Information System.

Anthropometric Data: ? indicates no information available; 1 - occasional survey-based data; 2 - regular clinic-based data. Nutritional Indicators: 1 - agricultural production; 2 - livestock levels; 3 - prices; 4 - marketing board transactions; 5 - meteorological conditions; 6 - food

aid; 7 - remotely sensed indicators; 8 - pest monitoring data; 9 - food entitlement indicators [e.g. income]; 10 - food acquisition coping strategy indicators).

1.1.3 The Zimbabwean National Health Information System

Zimbabwe's nutritional surveillance system is based on a growth monitoring programme of under-5 year olds, which was initiated in 1987 as part of the National Health Information System [NHIS] (Tagwireyi and Greiner, 1994). Prior to this, a system of growth monitoring for individuals had been operating since 1981 (Loewenson, 1991: p. 368). Children under 5 years are weighed at health centres throughout the country, as shown in Figure 1.1 and their weight-for-age is calculated. Typically, weight is measured using a torsion spring balance with a dial display. Such scales are capable of measuring weights up to 25kg, with a resolution of 100g (Tomkins, 1994: p. 108). The 0-4 year old age cohort was considered to be the most nutritionally vulnerable when the NHIS was established, so monitoring focussed on this group following standard recommendations (Beaton *et al.*, 1990: Ch. 6). Weight-for-age is used as the main anthropometric index in the system because it is considered a better predictor of subsequent morbidity and mortality in non-crisis situations than other indices, such as height-for-age (WHO Expert Committee, 1995: p. 210).

The information recorded is the total number of children measured in each of four age categories (under 6 months, 6-11 months, 12-23 months, and 24-59 months), together with the number whose weight-for-age falls below the third percentile of the NCHS standard population. Each child is given a health card, so that the progress of his/her growth can be monitored. This idea of using a growth card is based on a pilot study by Morley and Woodland (1979) in western Nigeria. They designed a 'road to health' card, which contained a graph with weight on the y-axis and age on the x-axis. Dietary and immunisation details were also recorded on the reverse of this form. In this original study, the card was found to be a useful aid in the early detection of malnutrition, in making recommendations about supplementary feeding, in identifying children at risk of malnutrition, and in involving and educating the mother in health aspects of childcare. In addition to these benefits, related to the individual, Morley and Woodland (1979) also suggested that information on the card could be used in epidemiological studies at the population level. The 'road to health' card was subsequently adopted and promoted by UNICEF, hence its widespread use throughout southern Africa (Ndauti, 1993). Growth monitoring formed part of UNICEF's 'GOBI' strategy for improving child health (this consisted of Growth monitoring, Oral rehydration therapy, Breast-feeding, and

Immunisation). Although the Zimbabwean system is based on the 'Road to Health' card promoted by WHO, several other variants on this system exist. For example, a Growth Surveillance card consisting of two different charts, which was developed in Africa, is also used in some southern African countries (Ruel *et al.*, 1991).

The Zimbabwean growth card enables the child's weight to be plotted as he/she grows older, as shown in Figure 1.2. The weight-for-age graph includes the major stages in a child's development (sitting, walking, talking) and a line that represents the third weight-for-age percentile of the standard National Centre for Health Statistics (NCHS) population. A child is classified as underweight if his/her weight-for-age lies below this line. This contrasts with other growth monitoring programmes, where coloured bands are used to depict the different centiles (for example, the Tanzanian Road to Health card has red, grey, and green bands). As such, the surveillance system is subject to the same criticism as others in sub-Saharan Africa in that it is designed primarily to monitor growth in individuals, rather than provide a standard for comparing different populations (Davies *et al.*, 1991).



Figure 1.1: A child being weighed for growth monitoring at a Zimbabwean hospital.

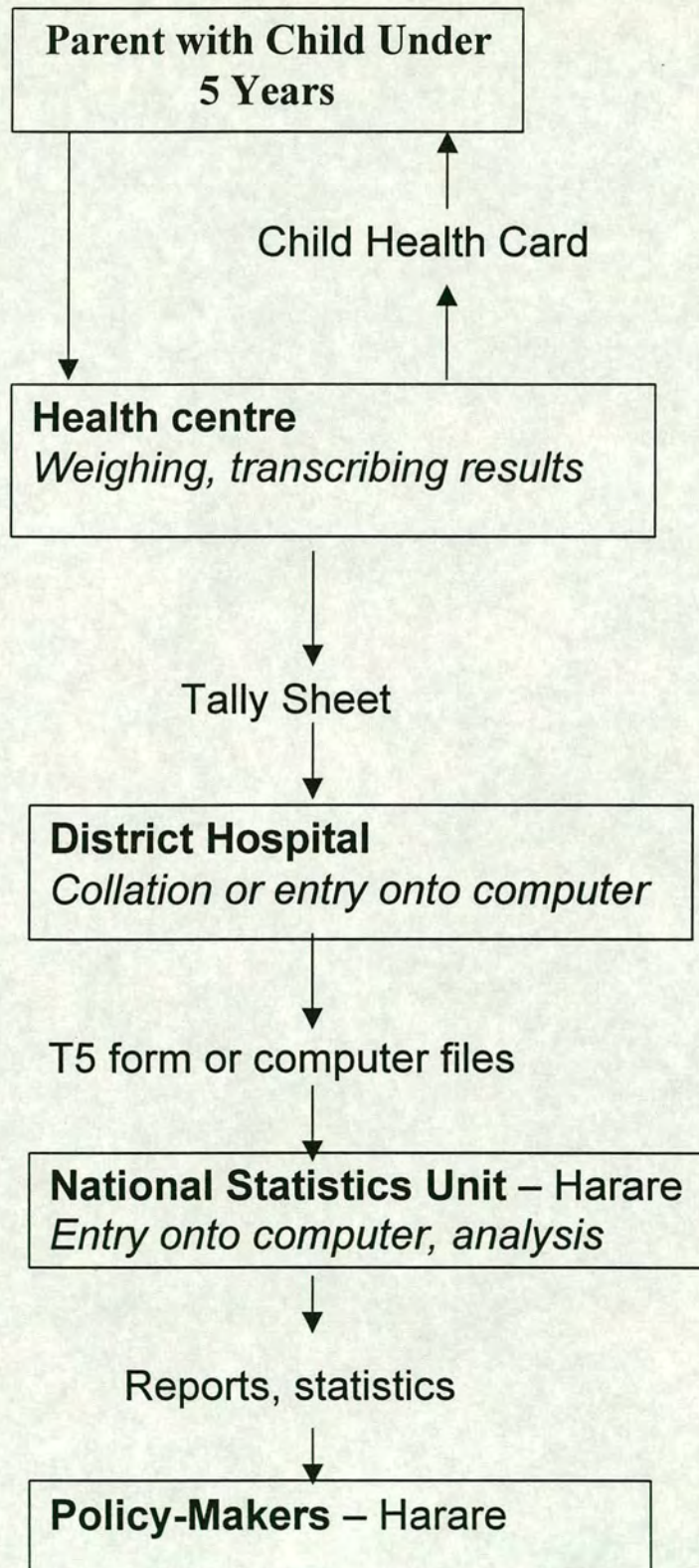


Figure 1.3: Flows of Growth Monitoring Data in the National Health Information System.

At the end of every month, each health centre submits a tally sheet to the district administrative headquarters, where the information was until recently transferred manually onto a summary sheet known as a T5 form (see Appendix 1). From the period 1988 to 1993, these monthly summary forms were then computerised in Harare. After 1993, this system was modified, so that in many areas the original tally sheet information was computerised locally within district hospitals, thereby reducing the risk of transcription errors. These flows of information are summarised in Figure 1.3.

1.1.4 Problems of the Zimbabwean growth monitoring scheme

The potential sources of error in such clinic-based growth monitoring schemes have been described elsewhere (Ruel, 1995). Two types of error can be distinguished: random errors, which increase variability in weight-for-age measurements, and systematic errors, which affect the mean of the weight-for-age measurements. One problem is measurement error, resulting from miscalibration or incorrect use of scales and inaccurate age assessment. Of these two sources of measurement error, inaccurate age assessment is more likely to affect the calculation of weight-for-age. When considering trends in large populations over several years, most of these problems, which are unlikely to lead to consistent under- or over-estimation of nutritional deficiencies, will more or less balance out. Kostermans (1994) has shown that such random errors lead to a slight over-estimate of the prevalence of poor nutritional status, but this effect is very slight compared to those resulting from systematic errors caused by sampling bias.

A second difficulty is sampling error, resulting from the fact that only those children who attend health centres are measured. Differences between those under-5s who participate in the formal healthcare system and those who do not will bias the estimate of the prevalence of under-nutrition derived from NHIS data. A survey by the Ministry of Health and Child Welfare in 1991 of 35,000 children under-5 indicated that 89% possessed Child Health Cards (Government of Zimbabwe, 1992). Although this indicated that the use of formal healthcare was widespread, the frequency of weighings under the programme declined from an average of 7 in the first year of life to a situation where most children were not weighed in the third, fourth, and fifth years of life. Thus, the most likely source of bias in the regional growth monitoring data is through differences in the frequency of attendance, rather than because of the small minority who do not participate in the programme whatsoever. This

frequency of attendance appears to vary, depending on the child's age, health status, and socio-economic characteristics. Since repeat visits for growth monitoring weighings are not recorded within the system, these differences in frequency of attendance cannot be eliminated from NHIS data.

The NHIS growth monitoring programme is also likely to be affected by transcription errors. Under the earlier system of data entry, these occurred firstly when information was entered onto tally sheets, secondly during copying from clinic tally sheets onto monthly summary forms and thirdly as monthly summary forms were computerised. Computer data entry screens were improved after 1993 to capture certain transcription errors (such as the number of children underweight being greater than the number weighed), but quality control procedures were more limited before this period. Under the present system of computerisation, these are now likely to occur only in tally sheet compilation and computerisation. As with measurement errors, transcription errors are unlikely to result in consistent over- or under-estimation of the prevalence of malnutrition.

The system is also subject to geographical errors, resulting from clinic attendees travelling considerable distances to visit health centres. This means that a sizeable proportion of the clinic attendees whose details are recorded on the district summary form may originate from outside the district in question. Bijlmakers *et al.* (1996: p. 51), for example, found that 15% of Zimbabweans by-passed their local health facility in favour of a more distant one. In addition, there may be people whose nearest facility lies in another district, further compounding this problem.

An ongoing debate in the literature about anthropometry concerns the use of appropriate reference populations and standards. The reference population used to define the cut-off point at which children are malnourished in the NHIS is the NCHS/WHO reference population, which consists of healthy Americans. Although Martorell (1985) has shown that privileged groups in most populations are capable of achieving the rates of growth in this reference population, African children may show different patterns of growth compared to other populations in the face of adverse conditions because of their different genetic composition. In addition, de Onis *et al.* (1997) have suggested that the NCHS/WHO standard itself has problems, since it contains a substantial number of obese children under the age of 5 years, who had received supplementary feeding from four months onwards. They note that children fed according to WHO recommendations have often failed to reach

the NCHS/WHO standard of growth and suggest that the standard itself should be revised to reflect more realistic, lower rates of weight gain with age.

The choice of children under 5 years as the population cohort to monitor can also be questioned. It might be argued that older individuals contribute more economically to household food security by earning income, farming, and carrying out household chores. There is thus an argument for monitoring adults, since any nutritional problems in this group will have repercussions for younger household members. The choice of children under 5 years for surveillance is generally justified on the grounds that this group is at most risk of nutritional problems. However, in fact it may be that other groups, such as young schoolchildren, are at as much or greater risk of nutritional problems, since they may have to walk long distances to school and miss meals whilst they are there.

Bani (1993) has also suggested that the chart on the card itself may be difficult to use and interpret. He suggests that not only does the mother have difficulty in understanding the information on the chart, but health workers may also have difficulty calculating age, and then plotting weight against age on the chart. The child's date of birth is recorded on the reverse of his or her health card, but the health worker still has to compute the child's current age before using the chart. Arithmetic and plotting errors made by tired or over-worked health staff are likely to reduce the quality of population-level data, but are unlikely to introduce much systematic bias. This is because whilst one health worker might consistently over-estimate prevalence of under-nutrition through erroneous use of the growth chart, a group of health workers on average will neither under- nor over-estimate underweight prevalence. The first problem, the lack of comprehension of the chart by mothers, has been highlighted by a study by George *et al.* (1993) in southern India. They found that there were no additional nutritional benefits for young children in adopting growth monitoring as well as a comprehensive set of health education measures. This brings into question the educational benefits of growth monitoring as suggested by Morley and Woodland (1979).

Anthropometry has also been criticised as being a 'late indicator'. In emergency situations, changes in indices such as weight-for-age only become apparent some months after the crisis has occurred, thus limiting its usefulness for 'early warning' of emergencies. This difficulty could be overcome by forecasting changes in underweight prevalence on the basis of other indicators, but this is seldom attempted in practice. Consequently, such anthropometric data tend to be used more for routine nutritional surveillance. At the

individual level, a similar debate exists concerning the usefulness of anthropometric indices for identifying those likely to suffer from subsequent increased mortality or morbidity. The relationship between the risk of illness or death and being underweight appears to vary from one population to the next (Pelletier *et al.*, 1993). In an analysis of results from six different anthropometric surveys from different areas, these authors found that mortality increased exponentially with weight-for-age, but baseline mortality varied from one data set to the next.

More generally, both nutritional information systems and famine early warning systems have been criticised for their failure to involve the communities concerned in the analysis and interpretation of data (Davies *et al.*, 1991). One alternative approach to this is community-based nutritional monitoring, which involves:

‘the results of a group of village children, expressed on wall charts for all to see, sometimes in a comparative, competitive way...’ (Tomkins, 1994: p. 114-115).

Buchanan-Smith and Davies (1995) have also argued that most studies on famine early warning and nutritional information systems concentrate on technical aspects of the system, rather than the use of the information produced. The few studies that have considered organisational aspects of information systems and the use of information generated have followed a participant-observer methodology (Pelletier and Msukwa, 1991).

Finally, nutritional information systems have also been criticised on the grounds that they seldom incorporate data from other sectors, either agricultural or socio-economic. Because growth monitoring data are collected at clinics, virtually no information is collected about the home environment in which the children being measured live. Since health, agricultural and socio-economic data collection are not integrated for the individual child, this means that the different streams of information must be integrated at the population level after collection. This partly explains the emphasis placed on integrating secondary data from different sources earlier in this chapter.

1.2 CAUSES OF POOR NUTRITIONAL STATUS

1.2.1 General causes

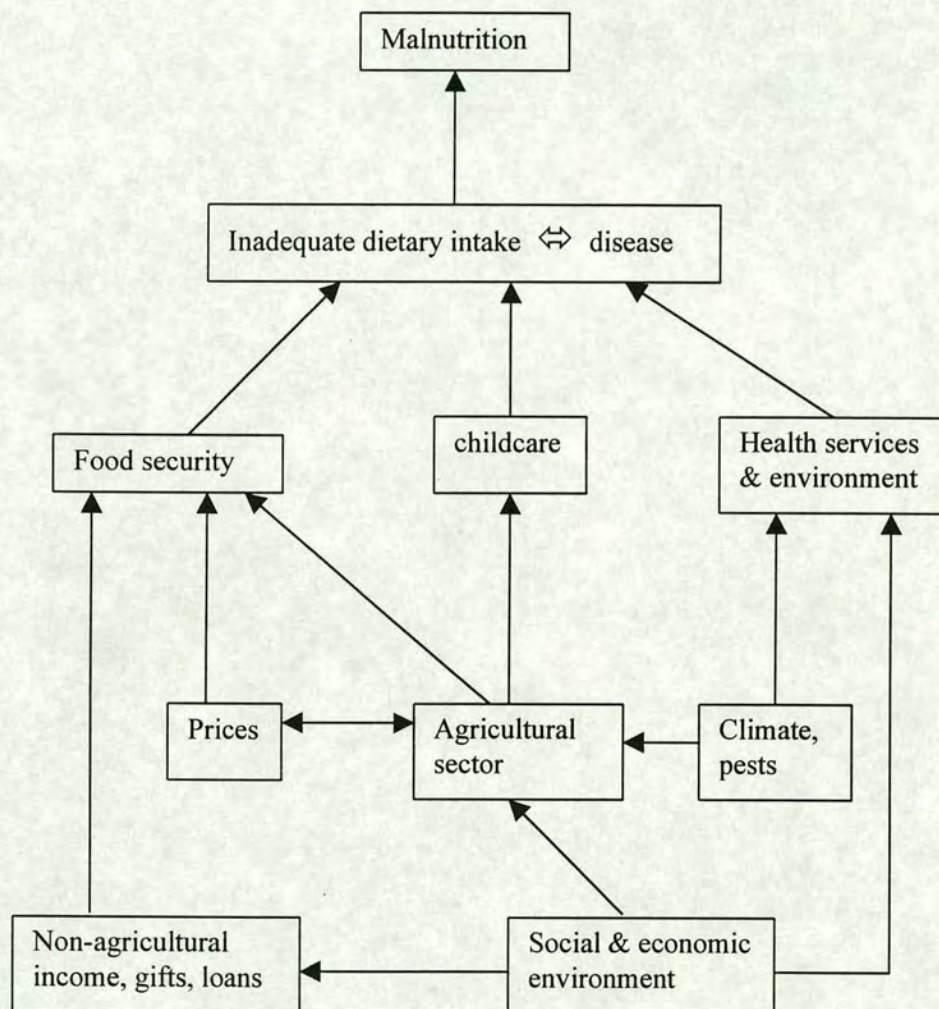


Figure 1.4: *Causes of poor nutritional status – a conceptual framework* (Adapted from Jonsson, 1995 and Mebrahtu *et al.*, 1995)

Figure 1.4 above shows the most significant causes of poor nutritional status among children. This diagram largely follows that of Jonsson (1995), but some agricultural linkages to nutrition have been added from Mebrahtu *et al* (1995). Two immediate causes are apparent from this diagram: inadequate food consumption (either in terms of energy or micro-nutrients) and disease. Disease affects nutritional status by reducing the body's ability to absorb nutrients, for instance by suppressing appetite or by disrupting digestive processes

in the gut. Looking beyond these immediate causes, food consumption by an individual can be disrupted by inadequate household-level access to food. This can occur either through a collapse of subsistence production or through a 'trade-based entitlement failure' (Sen, 1982: p. 2). In the latter case, the household's ability to purchase food through the market or acquire food in the form of welfare or gifts is inhibited.

At the same time, however, a child's health may also affect its nutritional status. This is influenced in turn by two groups of factors: the health environment and the provision of health services. The health environment includes factors such as the type of sanitation used by the household, the nature of their water supply, and their type of housing. It also includes the levels of disease pathogens in the environment, such as malarial *Anopheles* mosquitoes or bilharzia in standing water.

Both child health and food consumption are affected by patterns of maternal and childcare and intra-household decision-making. The pattern of distribution of food within the household is clearly important if children are to be adequately fed. Furthermore, in the case of small children, patterns of breast-feeding and weaning are extremely important. Weaning foods that are insufficiently rich in energy can be difficult to absorb and a period of growth faltering during weaning is common in many developing countries. Childcare also affects health status as well as food consumption, since the decision to make use of health facilities ultimately rests with a child's mother. Adequate knowledge of the treatment of childhood diseases and of simple preventative practices in, say, food preparation, is equally very important in maintaining nutritional status.

It should be noted that the conceptual model of the causes of poor nutritional status in Figure 1.4 shows environmental influences only, but not genetic ones. However, Tomkins (1994: p. 109) suggests that:

'Many studies now show that children of the majority of ethnic groups in the world can grow as well as international standards if they belong to elite socio-economic groups'.

This implies that whilst the nutritional status of an individual may be strongly influenced by genetic considerations, at population level environmental factors may be the major constraints on growth. Furthermore, one other influence on nutritional status not apparent in Figure 1.4 is energy expenditure. Higher energy expenditure levels resulting from greater physical activity increase the body's energy requirements and if these are not met then this can result in poor nutritional status.

1.2.2 Causes of poor nutritional status in Zimbabwe

Current patterns of under-nutrition prevalence in Zimbabwe are related to the historical development of the country's land use. Prior to the colonial period, population densities were much lower than in modern Zimbabwe and in many areas livelihoods were based on shifting cultivation coupled with hunter-gathering. Iliffe (1990: p. 111) has argued that the population during this period was better equipped to cope with periods of food shortage and that starvation was only widespread when these were coupled with violence or war. Following this period, a major redistribution of population took place. As more Europeans were encouraged to settle in Rhodesia, the indigenous population was forced onto more marginal land. These changes began with the creation of the Gwayi and Shangani reserves for the indigenous Ndbele in Matabeleland in 1894 and slowly spread eastwards into Mashonaland (Moyo, 1995: pp. 129-130). The more productive areas of colonial settlement became European Areas, whilst the more marginal areas of indigenous settlement became the Tribal Trust Lands where land was held communally. The pattern of land use thus reflected the racial segregation in Rhodesian society. Subsequently, the law was modified to allow some limited land rights to the indigenous population, and native Purchase Areas were established where indigenous Zimbabweans held private rights to more productive land. Under this colonial land use system, agricultural production on the poorer quality land in the Tribal Trust Lands was incapable of supporting the resident population. This meant that the local population was forced to supplement meagre subsistence production by migrating to towns, commercial farms and mining areas to earn additional income to buy food. The new land use pattern thus effectively created a pool of labour for the European Areas. A cyclical pattern of migration became common, in which men seasonally migrated out of the Tribal Trust Lands to earn income, leaving women to manage their fields. Older men would return to the Tribal Trust Lands to retire, having spent much of their working lives elsewhere as migrant labourers.

Following independence in 1980, the Lancaster House agreement guaranteed the land rights of white farmers in the European Areas. Land was redistributed on a willing buyer-willing seller basis, and the government purchased some of the former European farms for resettlement by small-scale farmers. Such land came to be known as the Resettlement Areas. The existing land use types were renamed: the Tribal Trust Lands became the Communal Areas, the European Areas came to be known as the Large Scale Commercial

Farming Sectors (LSCF), and the Purchase Areas came to be known as the Small Scale Commercial Farming sector (SSCF).

The persistence of the colonial land use patterns into post-Independence Zimbabwe means that the prevalence of underweight children still varies significantly by land use type. Loewenson (1986) has shown that levels of under-nutrition are generally lower in the SSCF sector and resettlement areas compared to the Communal Areas and LSCF sector. Overall, children in rural areas show poorer nutritional status compared to those in urban and mining areas, as shown in Table 1.2.

Land use sector	Age cohort	Weight-for-age ¹	Weight-for-height ²	Height-for-age ³
Communal Areas	0-6 months	27	9	51
LSCFS	0-6 months	59	12	33
Mining areas	0-6 months	14	2	23
Urban areas	0-6 months	0	0	0
Communal Areas	6 mths – 2 yrs	20	19	27
LSCFS	6 mths – 2 yrs	52	28	38
Mining areas	6 mths – 2 yrs	27	8	20
Urban areas	6 mths – 2 yrs	10	12	9
Communal Areas	2-5 years	29	7	24
LSCFS	2-5 years	14	8	25
Mining areas	2-5 years	20	5	10
Urban areas	2-5 years	4	6	6

Table 1.2: anthropometric indicators for different land use sectors in Zimbabwe (Source: Loewenson, 1986. All measures are percentage of age group based on the Tanner-Whitehouse anthropometric standard. ¹ based on those with weight-for-age less than 75% of reference median; ² based on those with weight-for-height less than 80% of reference median; ³ based on those with height-for-age less than 90% of the reference median).

Nutritionally vulnerable groups can also be identified across all of these land use types. One such group comprises refugees and immigrants. The LSCF sector has traditionally attracted migrant labour from Malawi and many of these workers, speaking a different language and devoid of kinship networks for assistance are nutritionally insecure (Amanor-Wilks, 1995). At the same time, Zimbabwe also has a large Mozambican refugee population as a result of the years of civil war. The Zimbabwean government set up five refugee camps for Mozambicans in 1984 in Manicaland province and many others moved over the border to work unofficially in Zimbabwe (Amanor-Wilks, 1995: pp. 52-53). By

August 1992, some 165,000 Mozambicans were living in Zimbabwe (Government of Zimbabwe, 1994e: p. 20) and despite the repatriation of many by the UN High Commission for Refugees, many others still remain. The problems of these refugees are similar to those of the more traditional migrant labourers: an absence of kinship ties, problems of language in some cases, and the fact that many arrived virtually destitute in Zimbabwe. The impact of these workers on host communities has also been noted by Amanor-Wilks (1995: p. 53 quoting a commercial farm worker):

‘At the time when they were battling in Mozambique, people fled from there seeking refugee status here in Zimbabwe. The tea estates just say, instead of giving them the actual pay, “we’ll give you Z\$60 a month”, when it’s supposed to be Z\$120 for farm workers’.

This perception that immigrants lower local wages isolates Mozambican refugees still further.

At the same time, other research suggests that the children of single or divorced Zimbabwean women may also be more likely to be under-nourished. Adams (1991) has shown that children of mothers who were casual workers in Masvingo and Chipinge districts were more likely to be below the third percentile of weight-for-age than other children. It should be noted that such households are different to split units where the father is absent but working as a migrant labourer and remitting money back to the rest of the household. Tagwireyi and Greiner (1994: p. 63) describe the reasons for the vulnerability of such households:

‘Despite government efforts, improvements in the status of women since Independence have been limited to a very few areas such as the legal status of women and the availability of drinking water. Women have less access to land, inputs, extension, credits, and income.’

Recent evidence from a longitudinal survey in a resettlement area in Murewa suggests that the divorce rate and therefore the number of such vulnerable households is increasing (Kinsey *et al.*, 1998).

The specific nutritional problems faced by Zimbabweans can also be identified through the conceptual model in Figure 1.4. Looking at the underlying causes in Figure 1.4, declines in household food security in Zimbabwe are generally related to one of two causes. The vast majority of subsistence agriculture is rain-fed, so any decline in production is usually related to drought. Exceptionally, pests such as red locusts and other adverse climatic conditions can also reduce yields. However, Iliffe (1990) and others have also shown that because of its historical development, Zimbabwe’s rural populations rely on market purchases for their staples more than their counterparts in most other southern

African countries. This means that the other likely cause of a decline in household food security in Zimbabwe is either a rise in the price of staples or a decline in the purchasing power of the household.

In terms of care, one of the biggest problems for Zimbabwean children has been growth faltering during the weaning period. Tagwireyi and Greiner (1994: p. 71) suggest that

‘Early growth retardation suggests that while children aged 2 to 5 are most vulnerable to malnutrition, it is during the 6-to-18-month period that active damage to nutrition occurs...Infants become susceptible to harm caused by household food insecurity when they no longer enjoy the cushion supplied by breast-feeding’.

This decline in nutritional status in infants results partly from the use of food supplements and water at a very young age. Many young babies under 6 months are fed water and semi-solids such as maize porridge too early to the detriment of their nutritional status. This goes against WHO recommendations, which advocate exclusive breast-feeding up to 6 months.

The factors influencing children’s nutritional status have also changed in recent years. Three new problems have arisen, all of which are likely to have an adverse effect on child nutritional status. In 1991/92 the country was affected by the worst drought of the century, in which maize production fell to only 21% of normal levels (FAO, 1992). At the same time, the prevalence of HIV/AIDS amongst Zimbabweans has been rising steadily since 1980. Recent estimates from the Honde Valley suggest that 35% of adults aged 25 to 29 are now HIV-positive (Gregson *et al.*, 1996: p. 2). Although the level of AIDS prevalence was difficult to assess, the Honde Valley study suggested that the incidence of parental death had doubled between 1980-1991 and 1992-1995 (*ibid.* p. 19). This increase in mortality had particularly affected men in the 25-44 year age cohort and was linked to an increase in the number of orphans since 1991. These trends are consistent with an increase in AIDS prevalence. These problems may have been exacerbated by the adoption of an Economic and Structural Adjustment Programme (ESAP) by the Zimbabwean government. This programme involves market liberalisation, austerity measures, and cutbacks in public expenditure. These new problems for child nutrition are discussed in greater detail in Chapter 5.

1.2.3 *Agriculture in Zimbabwe*

As noted earlier, the Zimbabwean agricultural sector comprises four main production systems: the Communal Areas, the small-scale commercial farming sector (SSCFA), the large-scale commercial farming sector (LSCFA), and the resettlement areas. The Communal Areas occupy some 16 million Ha, whilst the LSCFA comprises 11 million Ha, the Resettlement Areas 3 million and the SSCFA 1 million Ha (Moyo, 1995: p. 85). In terms of population, the Communal Areas are the dominant land use sector with 56% of the country's population, so the following discussion of agriculture concentrates primarily on this sector.

In the Communal Areas, most agriculture is for subsistence. These areas are typically low in rainfall, so crops grown tend to be drought-resistant. Most agriculture in this sector is rain-fed, though there are an increasing number of small holder irrigation schemes as well as numerous 'informal', farmer-initiated schemes (Manzungu and van der Zaag, 1996). Typical crops include varieties of pearl and finger millet, sorghum, peanuts (also known as groundnuts) and bambara nuts (also known as roundnuts). Millet and sorghum, often referred to as small grains, are often used for brewing beer, which can then be sold to earn income (Corbett, 1994). Since independence in 1980, these traditional crops have been replaced in some areas by white maize, which is less drought-resistant but can be more easily marketed for cash. For the traditional crops, most communal farmers used retained seed, but in the case of maize the majority of farmers buy in hybrid varieties (Friis-Hansen, 1995). Agriculture in this sector tends to be low-input, with relatively few households applying fertiliser and relatively little weeding taking place (IIED/FSRU, 1994).

Cattle form an important part of the farming systems in many of the Communal Areas, although in parts of northern Zimbabwe such as Dande the tsetse disease problem prevents cattle from being used (Lan, 1983). Cattle have many uses, but as Ndlovu and Francis (1997: p. 16) note:

'Provision of draught animal power is the single most important quantifiable function of cattle in communal areas'.

Cattle ownership can affect the timing of crop planting, since households without cattle often have to wait before hiring or loaning draught animals until wealthier households have finished using cattle for ploughing. Cattle sales also provide income in times of food shortage. In a survey of five communal areas in Manicaland province, Zindi and Stack

(1992: p. 303) found that 40% of households had sold cattle in the last five years during periods of food shortage. Traditionally, cattle are used to make bride-wealth payments or *lobolla* and this is another important motive for keeping cattle. In addition to cattle, goats are also an important type of livestock in the Communal Areas. Zindi and Stack (1992: p. 296) noted that 70% of households in their sample owned goats and a similar proportion owned cattle. Whilst draught power is the primary use of cattle, goats are often slaughtered for consumption or sold to earn cash.

Most of the land in the Communal Areas was sparsely populated prior to the colonial period and the vegetation reflects the intensification of a shifting cultivation system. Some land is now continuously cropped, whilst much of the land currently fallow shows signs of earlier cultivation. Typically, this land has reverted to thorny scrub and only the land along riverbanks and rocky outcrops remains forested (Campbell et al, 1989). These uncultivated areas are now used for grazing livestock.

In the LSCFA, the main crops grown are tobacco, cotton, sugar, and maize, though more recently attention has shifted to horticulture and spices such as paprika (Financial Gazette, 1998). In Zimbabwe's Eastern Highlands, LSCFA farms also cultivate tea and coffee (Amanor-Wilks, 1994). In drier parts of the country such as Matabeleland, extensive ranching of cattle also takes place and around Harare there are a number of dairying enterprises in this sector. In terms of area, the majority of LSCFA land is corporately owned and is divided up into 1,700 different enterprises. In addition, there are also 2,700 family-run LSCFA farms, which are typically much smaller in size and often run by families of European descent (Moyo, 1995: p. 84). On many commercial farms, a core workforce lives in one or more compounds on the farm property, though seasonal workers are often brought in during times of peak agricultural activity.

In the Resettlement Areas, the vast majority of programmes have emphasised the creation of uniform, family-run smallholdings, though a few schemes have been based around co-operatives or holdings organised around processing facilities (Kinsey, 1997). Most of the households assigned plots on resettlement schemes were given a standard 5 Ha plot for arable cultivation, plus a variable amount of grazing land for livestock. Agriculture on these resettlement schemes tends to be more commercial. Kinsey (1997: p. 10) notes that households in resettlement areas generally earn more than three times as much from livestock as their counterparts in Communal Areas and more than seven times as much from crops. The SSCFA, which occupies a relatively small proportion of Zimbabwe's agricultural

land, similarly consists of smallholders geared towards commercial agriculture. This sector has traditionally made a significant contribution to Zimbabwe's strategic maize reserves and maize production remains one of the major activities in the SSCFA (Jayne and Chisvo, 1991).

1.3 REVIEW OF ANALYTICAL METHODS FOR NUTRITION INFORMATION SYSTEMS

1.3.1 Descriptive analyses of underweight prevalence

The Zimbabwean government has several mechanisms by which the data gathered through the growth monitoring programme are routinely analysed using descriptive statistics. The Health Information Unit of the Ministry of Health and Child Welfare and the Health Statistics Section of the Central Statistical Office produce an annual report that summarises underweight prevalence by age cohort and by province every year (Government of Zimbabwe, 1993c). In addition, the same unit has produced occasional papers, which examine seasonality and trends within growth monitoring data (Government of Zimbabwe, 1994f). Quarterly prevalence rates for the different cohorts are smoothed using a moving average technique and then graphed over several years to reveal aspects of seasonality and long-term trends visually. Both these uses of the data involve descriptive statistics and do not attempt to integrate the nutritional data with information from other sources, such as agricultural data.

1.3.2 Integrated analyses - vulnerability mapping

One methodology that can be used to integrate under-nutrition prevalence statistics with data from other sources is vulnerability mapping (Hutchinson, 1993). Vulnerability mapping is commonly used to assess the likelihood of the population of a set of regions ceasing to be able to gain sufficient access to food. In this approach, information about nutritional status forms one of a series of factors comprising 'vulnerability', which are combined together to form a single index. This is justified on the grounds that the long-term average under-nutrition rate within a given population should be related to the vulnerability level as identified by such an assessment, if this genuinely reflects access to food. The use of vulnerability mapping is generally justified on the grounds that it is a suitable technique for situations where data are incomplete and of unknown accuracy. In some cases, it has

been used as a means of enabling those collecting secondary data sets to participate in their analysis and primarily as a teaching tool rather than a means of targeting food aid (Caldwell, 1993). In other cases, it has been seen as a preliminary tool intended to be the basis for further analysis (USAID, 1991).

Several methodologies exist for producing vulnerability maps. In Bangladesh, Currey (1985) mapped out administrative districts (*mousas*) which met a set of conditions defining vulnerability. He first identified three variables including land holding size per capita and proportion of hired agricultural labour in the workforce as the nationally available statistics which best represented vulnerability. Next he mapped the third of *mousas* which had the lowest land holding size per capita, the third of *mousas* with the highest proportion of hired agricultural labour, and so on. Finally, all three maps were overlaid to identify the *mousas* that fell into the most vulnerable third for all three indicators. This final map represented the most vulnerable districts in Bangladesh.

Vulnerable areas have also been mapped through the weighted overlay of sets of indicators (USAID, 1993a; USAID, 1993b; Hutchinson, 1993). First of all, indicators available nationally and considered to represent vulnerability are adjusted so that each indicator has the same maximum and minimum values and statistical distribution. This can be done in several ways:

- Each district can be ranked in order (highest to lowest) of vulnerability according to each indicator. The rankings can then be used instead of the original indicator values when the maps are overlaid (USAID, 1993a).
- The following formula can be applied to the original indicator values to produce new values for overlay, where each new set of indicator values has the same maximum and minimum (the Idrisi project, 1993: p. 42):

$$I' = (X' - M') * (I - M) / (X - M) \quad 0 \leq I' \leq 1$$

where I' = transformed indicator value, I = original indicator value, X' = transformed maximum indicator value, M' = transformed indicator minimum value, X = original indicator maximum value, and M = original indicator minimum value.

- Provided the distribution of each indicator is more or less normal, the following transformation can be used for standardisation (Dyson, 1996):

$$I' = (I - \mu)/SD \quad (\approx -3 \leq I' \leq +3)$$

where I' = transformed indicator value, I = original indicator value, μ = mean indicator value, and SD = indicator standard deviation.

This approach is taken by Dyson (1996: pp. 51-55) to calculate a Food Security Index for countries based on daily per capita calorie supply, proportion of cereal consumption accounted for by domestic production, per capita income, and socio-political stability.

Next, a set of weights is developed for each of the indicators to be used. Each indicator is multiplied by its weight and the results added together to produce the final vulnerability map. Several methods have been developed for assigning weights to the different indicators:

- USAID (1993a) gave each indicator a weight between 0 and 1, so that the sum of the weights for all the indicators equalled 1. Vulnerability map users agreed the weights through a panel discussion about the relative importance of the different indicators.

- Hutchinson (1993) used a technique known as the Analytical Hierarchy Process originally developed by Saaty (1977) to develop weights for mapping vulnerability in Haiti. The importance of each indicator was assessed relative to every other indicator by a panel of NGO representatives. Each pair of indicators was then assigned a score based on the following table (after the Idrisi Project, 1993):

less important					more important			
1/9	1/7	1/5	1/3	1	3	5	7	9
extremely	very	strongly	moderately	equally	moderately	strongly	very	extremely

The scores assigned to pairs of indicators can then be tabulated, as shown in Table 1.3.

Rating of the row factor relative to the column factor

Indicator	Distance to Water Source	Agricultural Production per Capita	Dependency Ratio	Housing Type
Distance to Water Source	1	1/3	1/3	5
Agricultural Production per capita	3	1	1	7
Dependency Ratio	3	1	1	7
Housing type	1/5	1/7	1/7	1

Table 1.3: an Example of a Pairwise Comparison for Assessing the Comparative Importance of Four Vulnerability Indicators (after the Idrisi Project, 1993).

This table can then be converted to a set of weights for each row by calculating the principal eigenvector. Taking each column in the table and summing its pairwise ratings can approximate this value. In Table 1.3, this would give a sum of 7.2 for the first column, 2.5 for the second and third columns and 20 for the fourth column. Each pairwise rating is then divided by the sum for the column and an average weight taken for each row (the Idrisi Project, 1993: 42-44). The fourth column in Table 1.3 would thus be divided by twenty, giving new values of 0.25, 0.35, 0.35 and 0.05 for each row respectively. Averaging across the rows in Table 1.3 would give final weights of 0.16 for distance to water source, 0.39 for agricultural production per capita and dependency ratio, and 0.05 for housing type. A second measure, known as a consistency ratio, can also be calculated which is a measure of the probability that the pairwise comparison ratings have been derived by chance (Saaty, 1977).

Once the weights have been derived, each indicator is multiplied by the corresponding weight and the resultant values added together. The sum of the values is then presented as a map, indicating the relative vulnerability of different areas rather than an absolute measure of vulnerability. Some authors (Dyson, 1996) have ranked the final vulnerability scores and presented these rankings instead of the vulnerability scores themselves in order to emphasise that the scores are a relative assessment of vulnerability and do not measure it in absolute terms.

1.3.3 Integrated analyses - forecasting systems

One method of forecasting food shortage or period of nutritional deficiency is the 'convergence of indicators' approach. This looks for consistent trends across a series of indicators as a means of forecasting an imminent decline in nutritional status. In this context, 'the function of an indicator is to provide information about the state of a system' (Kelly, 1994: p. 444). The details of the methodology differ, depending on the quality of information available. In situations of relative data abundance, cut-off points are defined either on the basis of a retrospective analysis of time series data or through analysis of longitudinal household level data. For example, Mason *et al.* (1987) have used National Nutrition Surveillance System data for Botswana for 1979-1983 to define cut-off points for an index of groundwater sufficiency for maize growth. Elsewhere, Haddad *et al.* (1994) have used primary survey data to define cut-off points for demographic and socio-economic indices such as dependency ratio¹. In situations where there are insufficient data to define cut-off points, trends in indicators rather than their absolute values are used to identify impending nutritional problems. As Kelly, 1992: p. 445 notes:

'Many variables are used for early warning and targeting even though all that is really known about them is their likely direction of change as food insecurity intensifies'.

Under this 'convergence of indicators' approach, the monitoring system initiates preventative action when several indicators either simultaneously fall below their designated cut-off points or simultaneously show trends indicative of declining nutritional status.

Quinn and Kennedy (1994) have given two reasons for the relatively simple, bivariate nature of the approach:

- The simplicity of the technique facilitates rapid data interpretation so that the relevant organisations can act early to prevent the predicted decline in nutritional status.
- The data used are generally of poor or unknown accuracy, which makes multivariate analysis problematic.

1.3.4 Food balance sheets

The food balance approach to predicting nutritional status was originally developed by FAO for use in its Global Information Early Warning System and subsequently applied to over forty African countries (Davies *et al.*, 1991). Food balance sheets are used to quantify national food deficits or surpluses for food aid planning, rather than for prediction of changes

in malnutrition rates per se (Davies *et al.*, 1991), although the technique can be adapted to this end. It involves the calculation of aggregate food availability based on an assessment of food supplies and food deficits. Food supplies are calculated from opening stocks, production, and imports, whilst food deficits are calculated from exports, domestic consumption, and closing stocks. Non-food uses of both vegetable and animal products, such as retention for seed and animal feed production, are generally subtracted from the total available for domestic use. Disparate vegetable and animal products are converted to calorific equivalents using tables of calorific content. These have been calculated for eastern and southern Africa by the Wageningen Agricultural University Technical Centre for Agricultural and Rural Co-operation (West, 1987). Food balance sheets are usually applied at the national level, though attempts have been made to adapt the methodology to provincial and district levels. Such efforts have been based on assessing income levels together with subsistence production and then converting income into calorie equivalents using current staple prices (Farmer, 1993).

The resultant estimate of food available for domestic consumption has been compared with estimates of human energy requirements (James & Schofield, 1990). To make this comparison, an allowance for losses during distribution is subtracted from the estimate of per capita calorie availability. As Bender (1994, p. 388) notes 'these are little more than educated guesses and their accuracy is quite low' but relative to other food losses, their contribution is 'moderate'. An additional household allowance is also subtracted, which covers storage losses once the food has reached the household and food wastage by the household. Estimates of storage losses for rural households in developing countries vary enormously from 10 to 40% (James & Schofield, 1990), making this stage in balance assessment one of the most likely sources of error.

Human energy requirements can be calculated from the age-sex structure, weight characteristics, and activity patterns of the population concerned. For children and infants under the age of 10 years, energy requirements are calculated using equations that are based on age, sex and weight (James & Schofield, 1990). For adolescents and adults, a Basal Metabolic Rate (BMR) is calculated based on age, weight, and sex and this is combined with an estimate of Physical Activity Level (PAL) to give an assessment of energy requirements.

¹ Dependency ratio: the ratio of active household members to non-active members such as children and the aged.

After adjustments for pregnancy and infection, energy requirements are then multiplied by the population in each age-sex cohort and summed.

1.4 HYPOTHESES

Hypotheses related to this thesis thus cover three areas, following the perspectives outlined at the beginning of this chapter. A general hypothesis relates to the use of secondary data:

- A. Analysis of primary and secondary data may reveal alternative apparent causes of poor nutritional status: it is possible to reconcile conflicts between these different sources of data through an integrated analytical approach.

Secondly, there are hypotheses that relate to information systems:

- B. The National Health Information System's growth monitoring programme provides useful and accurate information concerning the nutritional status of children under 5 years.
- C. Prediction of nutritional status is possible from secondary data alone, without the need for household or rapid rural appraisal surveys.

Thirdly, there are hypotheses concerning nutritional status:

- D. The combined effects of the Economic and Structural Adjustment Programme, the HIV/AIDS epidemic, and drought have increased the proportion of children suffering from poor nutritional status since 1991.
- E. The peak season for nutritional problems in Zimbabwean children is immediately pre-harvest in January-March, when food security is low and diarrhoea and malaria rates are high.
- F. High prevalence of underweight children is related to health factors as well as food security. Health factors in this context includes both measures of the health environment (such as type of sanitation and water source) and morbidity per se (as measured by disease rates).

Figure 1.5 gives an overview of the chapters in the thesis and illustrates how these relate to the hypotheses described above.

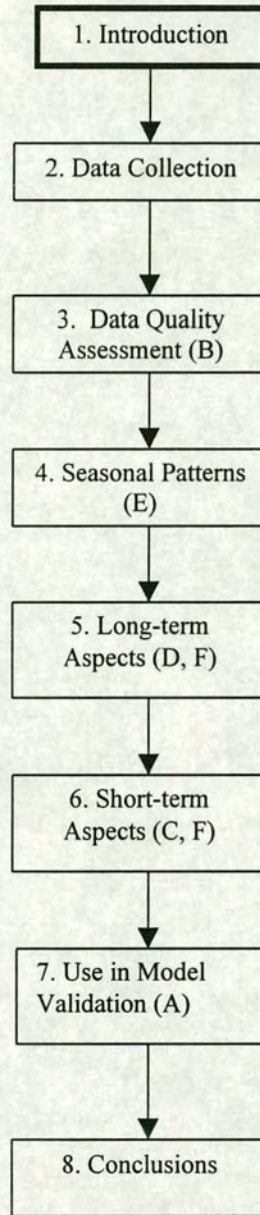


Figure 1.5: An overview of thesis chapters (letters in brackets indicate the hypotheses explored within each chapter).

2. Data Collection Strategy and Pre-Processing

2.1 *Introduction*

The approach adopted in the study consisted of three components, which formed part of the project 'An Integrated Model of the Food System in a Region of Zimbabwe' (hereafter referred to as the IMFS project):

- A. The collation of secondary data of relevance for nutrition at national level.
- B. The collation of more detailed secondary data for one particular district, Buhera, which lies in Manicaland Province.
- C. A detailed longitudinal questionnaire survey of households in Buhera district.

The more detailed study of Buhera was undertaken to gain insights into the processes involved in secondary data collection in a rural area. It also provided an opportunity to identify potentially useful data sets held at district level, but not collated centrally in Harare. The fact that the secondary data gathered for Buhera district also coincided with the questionnaire survey enabled an exploration of the issues involved in linking primary and secondary data. Buhera was chosen for the questionnaire survey because it is regarded as one of the poorer districts in Zimbabwe and therefore has significant problems of child nutrition (FEWS, 1994). In addition, the district comprises three agro-ecological zones and patterns of farming vary according to this environmental gradient. It therefore provided an opportunity to assess the relationship between farming system and nutrition within the IMFS project. A final reason for selecting Buhera was its relative accessibility from Harare.

Secondary data concerning nutritional status in Zimbabwe were gathered from three sources: the World Wide Web; from the Zimbabwean capital, Harare during field visits between 1994 and 1996; and from two towns in Manicaland province, Mutare and Buhera. Information gathered in Harare and through the web covered the whole country, whilst the information gathered in Manicaland concerned Buhera district only, as described in more detail below.

2.2 Collation of National Secondary Data

Much of the information collected also formed part of the IMFS project and so many different project team members undertook data collection. The characteristics of the national data sets collected, including the individuals responsible for their collation, are shown in Tables 2.1 and 2.2.

2.2.1 Review of Secondary Health and Nutrition Data

The central data set used in this thesis to provide insights into under-nutrition prevalence was the National Health Information System (NHIS) growth monitoring information. Two colleagues on the IMFS project, Patricia J. Mucavele and Mrs. J. Nyatsanza, obtained growth monitoring information from the Zimbabwean Ministry of Health and Child Welfare for the periods from January 1988 to March 1993 and from January 1994 to December 1995. This information was available for 57 districts throughout Zimbabwe from the NHIS and was also broken down into four different age classes (0-5 months, 6-11 months, 12-23 months, and 24-59 months). The data were provided as a set of dBase IV files. As well as anthropometric information, the same NHIS data set also covered reported cases of major diseases (such as malaria, measles, and bilharzia) and immunisations. All of this information was provided on a monthly basis. The break in the time series from April to December 1993 was related to changes in the design of the T5 form used to collect health statistics. There appeared to have been a disruption to the data collection and entry system whilst computer programs and data entry screens were updated to reflect the layout of the new form. Subsequent to these meetings, the Africa Data Dissemination Centre has also made these data available at:

<http://edcintl.cr.usgs.gov/bin/ftpadds/a=mohd/b=zi>

Data set	Temporal resolution	Spatial Coverage	Spatial resolution	Collated by:	Responsible organisation	Availability
Food aid demand and deliveries	Monthly (though quarterly in parts)	Nation-wide, except Manicaland Province	District	P J Mucavele	Department of Social Welfare	1980-May 1993.
Livestock numbers	Annual	Only includes LSCFS post-1992	Communal Area	J Wright, P Vaze	Veterinary Services Department	1983-1994.
NDVI	Dekadly	Nation-wide	49km ² pixel	J Wright	Africa Data Dissemination Service (USGS)	1981-91
Health statistics	Monthly	Nation-wide	District	P J Mucavele, J Nyatsanza	Ministry of Health and Child Welfare	1988-1995
Arable Production	Annual	Communal Lands only	Communal Area	A Conroy, J Wright	Agritex / NEWS	1981-93.
Arable Production	Annual	All other land use sectors	Province	J Wright, P Vaze	Central Statistical Office	1981-1995
CCD	Dekadly	Nation-wide	7km pixel	J Wright	REWS	Sept 1988 – 1995.
Rainfall	Dekadly	Nation-wide, but biased towards LSCFS	Rainfall station	J Wright	Meteorological Department / USGS	1972 – mid-1992
Maize consumer prices	Monthly	Communal Lands only	167 markets in Communal Areas	J Wright, P Vaze	Agritex / NEWS	July 1991 – October 1994

Table 2.1: Characteristics of regularly collected secondary data for Zimbabwe (NDVI – Normalised Difference Vegetation Index, a measure of 'greenness' of vegetation derived from satellite imagery; CCD – Cold Cloud Duration, a proxy measure for convectional rainfall derived from satellite imagery)

Data set	Temporal resolution	Spatial Coverage	Spatial scale or resolution	Collated by:	Responsible organisation	Temporal availability
Census	Every 10 years	Nation-wide	District / ward	J Wright, S. Kudhlande	Central Statistical Office	August 1992
Crop land use intensity	Available for one time point only	Nation-wide	1km grid square	J Wright	USGS Africa Data Dissemination Service	Not documented
Vegetation type	Available for one time point only	Nation-wide	1km grid square	J Wright	USGS Africa Data Dissemination Service	Not documented
Road network	Available for one time point only	Nation-wide	1:1,000,000	J Wright, S Gundry	World Resources Institute	Revised 1983-86
Rail network	Available for one time point only	Nation-wide	1:1,000,000	J Wright, S Gundry	World Resources Institute	Revised 1983-86
Administrative boundaries	Available for one time point only	Nation-wide	1:1,000,000	J Wright, S Gundry	USGS Africa Data Dissemination Service	August 1992
Agro-ecological zones	Available for one time point only	Nation-wide	1:1,000,000	J Wright, S Gundry	Department of the Surveyor-General	1965
Elevation	Available for one time point only	Nation-wide	30 km ²	J Wright, S Gundry	Australian National University	Not documented

Table 2.2: Characteristics of infrequently collected secondary data sets for Zimbabwe

In addition to these health-centre based surveys, I also collected data for a cross-sectional, community-based health survey, one of the Demographic and Health Surveys (DHS) that were funded by the US Agency for International Development. Globally, three rounds of surveys (referred to as DHS I, II, AND III) were carried out, but only two of these took place in Zimbabwe. The first, DHS I, took place between September 1988 and January 1989 and covered AIDS, child anthropometry, pill compliance, maternal employment, and service availability (Macro International, 1990). The second, DHS III, took place between July and November 1994 and covered AIDS, child and maternal anthropometry, maternal mortality, pill compliance, and service availability (Macro International, 1995). This last survey is available over the Internet and comprises interviews with 6,128 women. Demographic and Health Survey (DHS III) information was downloaded from the appropriate web site (www.macrint.com/dhs/ftp/ftphome.html) following the granting of permission by the data holders, Macro International Inc.

2.2.2 Review of Secondary Agricultural Data

As described in Chapter 1, agricultural production and food purchases through the market affect food security at household level and the nutritional status of household members. Four major areas of secondary agricultural data are potentially available in Zimbabwe, which shed light on this area. These concern arable production, livestock, consumer prices for grain, and operations by the parastatal grain trading body, the Grain Marketing Board (GMB). Information about crop production is collected annually by Agritex, the extension department of the Ministry of Agriculture, Lands, and Water Resources as part of an initiative known as the National Early Warning System (NEWS, as referred to in Table 1.1). This project aims to provide timely warning of impending food crises by supplying decision-makers with appropriate information. These Agritex production estimates are available for the Communal Areas only; production in other sectors is monitored by the Central Statistical Office or CSO (Government of Zimbabwe, 1994a; Government of Zimbabwe, 1995a). CSO has also conducted occasional surveys in the Communal Areas, but these are based on small samples and are unsuitable for analysis below the province level (Government of Zimbabwe, 1996). The production statistics for other land use sectors are similarly only published aggregated to province level, and are therefore unsuitable for a district-level analysis. Until 1993, Agritex only produced aggregate figures for each Communal Area, but since then production figures have been produced by ward. The Agritex estimates are based on crop-walking and interviews with a set of ten

representative farmers in each ward, which are conducted by extension workers. Eight crops in total are monitored: small grains (sorghum, mhunga, and rapoko), maize, groundnuts, soyabeans, sunflower, and cotton. Information on crop production and yields in the communal lands were taken from the U.S. Geological Survey's Africa Data Dissemination Service at:

<http://edcintl.cr.usgs.gov/adds/data/agri/agri.html>

These data, which are available by Communal Area, were originally produced by Agritex, Makombe Building, Harare. Dr. Anne Conroy obtained additional yield and production data for 1993 by ward from Agritex in Harare.

Secondary agricultural data are also available in Zimbabwe covering livestock, since the Veterinary Services Department undertakes a census of livestock numbers annually. This census covers cattle, goats, donkeys, sheep, pigs, and horses. This information was gathered by myself and Prabhat Vaze of the IMFS project in 1995. Chris Ncube of the Veterinary Research Services Department, Borrowdale Road, Harare provided livestock numbers in dBase IV format, with the permission of Peter Gamble of the same department. Unlike the crop production estimates compiled by Agritex, this census has covered all land use sectors since 1993, though before this date large-scale commercial farm animals were enumerated separately. Census results are available digitally at a sub-district level, either by communal land, resettlement area, or commercial farming area. Potentially, therefore, the broader coverage of the livestock census should provide more representative agricultural information than the Agritex crop production estimates. However, in practice, there were problems with the livestock census in past years. Reporting of livestock figures in many areas is sporadic and with a few exceptions, only the larger communal areas consistently return livestock figures year after year. Figures for individual areas show enormous variability from one year to the next, raising doubts as to the accuracy of population estimates. The estimated size of the goat population in particular varies greatly between years. This variability may be a result of the way in which the census is implemented. In the Communal Areas, the number of livestock brought to dip-tanks is counted over a set period and farmers are interviewed about any other livestock they own. This information then forms the basis for the census return. However, since few farmers dip smallstock (goats, sheep, etc.), those who possess *only* sheep or goats are not generally involved in the census, since they tend not to appear at dip-tanks. In addition, the area codes follow a different system to that used by most other government ministries and many of the smaller reporting units were difficult to locate. Consequently, although the livestock census is a large data set

covering many years, only a relatively small proportion of the statistics it contains can usefully be related to nutritional data.

The third set of agricultural data of relevance to nutrition is consumer prices for basic staples. These data are again collected by the National Early Warning Unit in Agritex and cover consumer maize meal prices at a sample of markets around Zimbabwe (Government of Zimbabwe, 1993a). I also collected this information, with some assistance from Prabhat Vaze. Although the data collection system continues to operate, analysis and computerisation of this information ceased in late 1994, though the data collection mechanism remained in place. Consequently, a historical archive of monthly prices running from 1991 to 1994 is the only data available in practice. As with the crop production statistics, the information only covers the Communal Areas. The system covers a total of 61 Communal Areas, with the retail price of a 20 litre bucket of maize grain being gathered for three markets in each. As with the livestock census, this information also has its problems. These include the following:

- Although more than 150 markets are involved in the system, prices are collected only sporadically from these. Thus, the markets visited vary from one month to the next, making it difficult to compare monthly prices and to compile district-level price estimates.
- The markets visited are almost impossible to locate, since the computerised data set contains neither place-names nor co-ordinates for the different markets. Although a numeric coding system has been used, this bears no relationship to that used in other Zimbabwean data sets. This makes the NEWS price archive virtually impossible to use, except on an aggregate basis for the whole country.

Prices are also collected by CSO, but these are available at national level only and are not available digitally. These prices are intended for use by industry, rather than for early warning (Government of Zimbabwe, 1994b), although the Retail Price Index figures produced by CSO do provide a means of adjusting the NEWS maize prices for inflation.

The fourth source of potentially useful agricultural data is the GMB. The parastatal publishes annual producer prices for grains, which remain constant throughout the agricultural year and across the country (Jayne and Chisvo, 1991). In addition, the GMB also maintains a database of buying and selling transactions, plus transfers of grain between

its network of depots. Unfortunately, I was unable to obtain access to these records owing to their commercial sensitivity.

In summary, some general characteristics can be noted for these agricultural data sources. Firstly, *dis-aggregated* agricultural statistics are available for the Communal Areas, but seldom for other land use types. Although livestock and crop production figures are available for the large and small-scale commercial sectors through CSO, these are only available at province level (Government of Zimbabwe, 1994a; Government of Zimbabwe, 1995a). Secondly, whilst information is gathered about agricultural production, little useful information is available concerning access to food through markets. This is particularly important in Zimbabwe, where most communal farmers have to supplement their own production with market purchases of staples (Vaze *et al.*, 1996). These problems mean that out of the four potential agricultural data sets available for Zimbabwe (arable production and yields, livestock numbers, consumer prices and GMB transactions) only the arable production data and livestock numbers could be related to growth monitoring data.

2.2.3 Review of Secondary Socio-Economic Data

Basic living conditions are another important determinant of nutritional status. There are two main sources of socio-economic and demographic data for Zimbabwe at sub-national level. These are the 1992 population census and the Department of Social Welfare's records of drought relief operations. Although there are other data sources available at national level, such as the Household Income and Expenditure Survey undertaken by CSO in 1987, these do not provide information at province or district level across the country (Government of Zimbabwe, 1994d; Government of Zimbabwe, 1995b). Such generalised, aggregate information is difficult to integrate with the anthropometric data collected by the Ministry of Health and Child Welfare.

Patricia J. Mucavele from the IMFS project collected data on drought relief operations. The Department of Social Welfare has kept records of drought relief requests and deliveries by district ever since the government initiated a Drought Relief Programme in the early 1980s (Government of Zimbabwe, 1994c). The requests for government relief form an indication of community level stress and consequent nutritional problems. Lenneiye (1991: p. 69) has described how the food is allocated under the Drought Relief Programme: 'Families in need of drought relief register with the VIDCO [Village Development Committee] Chairman who then forwards the list to the Ward Councillor who compiles a list

for the six villages in a ward. These ward requirements are submitted to the District Drought Relief Committee, which compiles a district report for the Provincial DRC [Drought Relief Committee]... Food is requisitioned from the GMB [Grain Marketing Board] by the National Drought Relief Co-ordinator and it is taken to district distribution points by drought relief staff. Councillors then assist with food distribution (10kgs of maize per person per month).’

Unfortunately, several problems exist with these food relief requests, or ‘previews’, as a measure of community stress. Such difficulties include:

- Local communities have numerous other responses to food shortage, apart from demanding government assistance. Corbett (1988) has documented a wide range of ‘coping strategies’ used to acquire food in times of shortage, most of which do not rely on external assistance.
- The food allocation system is open to abuse: the Government of Zimbabwe (1994c), for example, note that the number of individuals requesting drought relief in some districts has exceeded the total population living there! Lenneiyé (1991: p. 71) describes one incident, ‘the fraud-related inquiry of 1985-86 (the Paweni saga)’ and suggests that the system is over-reliant on local politicians and lacking in accountability.
- Another difficulty is that only those meeting a predetermined set of criteria that define need are eligible for drought relief. These criteria are inconsistently applied over time and ‘re-screening’ of drought relief applications is sporadic due to personnel shortages. Therefore, requests for drought relief are a function of both actual need and administrative processing.
- Fourthly, grain distributed as drought relief is not the only form of aid available. The Drought Relief Programme also comprises a Food for Work Programme, a Public Works Programme (both still relatively small-scale) and a child supplementary feeding programme, run by the Ministry of Health and Child Welfare (Lenneiyé, 1991: p. 68; The Herald, 1994). This latter programme would be especially useful for investigation in relation to the growth monitoring programme, since it targets children under 5 years old. However, information about the scheme is unavailable from the Ministry of Health and Child Welfare at present. At other times, particularly during the 1991/92 drought, food aid has also been provided by NGOs (e.g. Christian Care, Save the Children Fund, and the International Red Cross) and through a school feeding programme (UNICEF, 1993).

Despite these problems, the drought relief previews provided one of the few measures of community stress on an annual basis.

Another source of socio-economic data is the national population census, carried out in August 1992. As well as covering demographic characteristics of the country's districts such as age-sex structure, the census also provides information about living conditions. In particular, the census covers type of water source, type of housing, and type of sanitation, all of which may be related to nutritional status. These basic household characteristics are recorded so that the government can assess the extent to which it is achieving its post-independence goal of increasing living standards throughout the population. Samuel Kudhlande from the IMFS project and myself collated and entered these data. Spatial units such as provinces, districts and wards corresponding to the attribute data in the census reports can be downloaded from the Africa Data Dissemination Service with co-ordinates in geographical latitude and longitude at:
<http://edcintl.cr.usgs.gov/adds/adds.html>

2.2.4 Review of Secondary Environmental Data

Debbie Strathearn, working for the IMFS project, visited the Department of Meteorology in Harare to obtain historical precipitation data for Zimbabwean meteorological stations. However, the Department were only prepared to release such information on paper and not in a digital format. Consequently, monthly precipitation data were obtained on paper for the Buhera meteorological station only for the period 1940-1995 and computerised and digital rainfall data were sought from other sources. The two main sources of digital rainfall data were the USGS African Data Dissemination Service (ADDs) and National Oceanic and Atmospheric Administration (NOAA). Rainfall data are in two forms: since June 1995, NOAA has created raster rainfall maps for every dekad¹, interpolated from meteorological station measurements using both elevation and Cold Cloud Duration satellite imagery. These data are available from:

<http://nic.fb4.noaa.gov/products/fews/precip.html>

Prior to this period, up until June 1992, the ADDs also holds precipitation measurements for approximately fifty Zimbabwean meteorological stations for each dekad. Measurements for a further twenty or so meteorological stations just over Zimbabwe's borders with Zambia, Botswana, South Africa, and Mozambique also provide some insight into rainfall patterns within the country. These data are available from:

¹ A *dekad* is a 10-day period.

<http://edcintl.cr.usgs.gov/adds/data/rain/rain.html>

This dekadly rainfall data set covers the same stations and time period as the monthly rainfall data set provided by the Global Historical Climatology Network of the National Climatic Data Centre at:

<http://www.ncdc.noaa.gov/ol/climate/research/ghcn/ghcn.html>

However, the major difficulty in using the precipitation data pre-1993 is caused by the locations of the meteorological stations. Most of the stations are located either in Zimbabwe's cities or commercial farming areas, so very little rainfall data are available for the Communal Areas. Ways of overcoming these difficulties are considered in Chapter 6.

Long-term average precipitation data were taken from the CD-ROM entitled 'Topographic and Climatic Database for Africa', produced by the Australian National University and described at <http://cres.anu.edu.au/software/africa.html>). These data had already been interpolated to a raster grid with a resolution of 0.067 degrees based on meteorological station data for 1920 to 1980 and elevation.

Zone	Description	Annual rainfall	Recommended production system
I	Specialised and diversified farming	Over 1,000 mm	Forestry and plantation agriculture (tea, coffee, macademia nuts)
Ila	Intensive farming	750-1,000 mm	Intensive farming with crops and/or livestock – few dry spells.
Ilb	Intensive farming	750-1,000 mm	Intensive farming with crops and/or livestock – higher risk of dry spells
III	Semi-intensive farming	650-800 mm	Livestock production with fodder crops and cash cropping.
IV	Semi-extensive farming	450-650 mm	Livestock production with some drought-resistant crops
V	Extensive farming	Under 600 mm	Extensive cattle or game ranching

Table 2.3: *Agro-ecological zones of Zimbabwe* (adapted from Government of Zimbabwe, 1984).

In addition, I digitised an agro-ecological zone map for Zimbabwe from a paper 1:1,000,000 source map. Six different zones are distinguished on the basis of climate, vegetation, soil type, and agricultural production system – the latter clearly being an important influence on nutrition. The characteristics of these zones are given in Table 2.3 and their distribution is shown in Map 2.1. The map, which was published in 1984 and based on a Transverse Mercator projection, was digitised in the Arc/Info GIS, transferred to

the Idrisi GIS, and subsequently converted to latitude and longitude co-ordinates for consistency with other map layers for Zimbabwe. One of the major difficulties with this map is its currency, since the map was last revised in 1984. There is some dispute over how far rainfall patterns have changed since this date. Some have argued that rainfall patterns in Zimbabwe changed since the mid-1980s (Kinsey, *pers. comm.*). However, in terms of national rainfall patterns, Gommers and Petrassi (1994: p. 16) suggest that there is 'no marked negative trend in rainfall' for a group of African countries including Zimbabwe. The Zimbabwean rainfall time series shows a slight increase up to 1979 and a slight decline thereafter (*ibid.*, p. 13). It is therefore unclear whether the 1965 agro-ecological zones map still reflects the geographical distribution of rainfall within the country.

Rainfall data were supplemented by satellite imagery, which provided an index known as Cold Cloud Duration or CCD. The use of this imagery is discussed in greater depth in Chapter 6. Following meetings with Graham Farmer and Camille van der Haarten of the FAO's Regional Early Warning System in Harare, CCD estimates derived from the NOAA Advanced Very High Resolution Radiometer (AVHRR) platform were obtained for Zimbabwe. These images are available dekadly (i.e. every ten days) and estimate the duration of cumulonimbus or thunderstorm clouds to the nearest half-hour. The time series of data ran from 1988 until 1995 and the images were converted to Idrisi format from the Image Data Analysis package (IDA) used by FAO. In this imagery, cold clouds are identified using the infra-red band from the AVHRR sensor based on estimated cloud top temperatures of 235°K or colder. Such images are used for computation of convective precipitation estimates. More recent cold cloud data from the Meteosat 6 satellite are available over the web from 1995 onwards from the National Oceanic and Atmospheric Administration (NOAA) at: <http://nic.fb4.noaa.gov/products/fews/cct.html>

2.2.5 Review of Secondary Infra-structural Data

Finally, several data sets were collated that related to the country's infra-structure. A 1:2,500,000 scale map of the GMB's network of storage depots was digitised. Maps of the country's road and rail network were taken from a CD-ROM provided by the World Resources Institute, which makes use of the Digital Chart of the World (DCW). The original source is a set of Operational Navigation Chart map sheets produced by the U.S. Defense Mapping Agency at 1:1,000,000 scale. All of these maps have been declassified and are now freely available with co-ordinates in degrees of latitude and longitude as part of the Digital

Chart of the World. Sheet numbers and compilation details of these maps are given in Table 2.4, indicating that they have not been revised for over ten years. However, whilst the rail network had remained largely unchanged since the original paper maps were revised, an assessment of the road map's accuracy in Buhera suggested that it failed to capture major changes in the road network (see below). As with the agro-ecological zones map, the value of the road map layer was limited by the fact that it was not current.

	Sheet numbers			
ONC Charts	N04	N05	P04	P05
Date compiled	11/71	4/73	1/86	11/71
Date revised	3/83	1/86	1/86	11/83

Table 2.4: Characteristics of source maps used for roads, rivers, and railways in Zimbabwe (source: World Resources Institute, 1995).

2.2.6 Problems in Zimbabwean Secondary Data

Aside from the general problems of working with secondary data outlined in Chapter 1, the discussion above suggests that there are several features that are specific to southern African data and others specific to Zimbabwe. Features common to other parts of southern Africa include:

- Firstly, with some of the information sources described, data are incomplete. For example, reporting of consumer grain prices is sporadic, making it harder to discern trends. The 1991/92 drought took place mid-way through the price monitoring exercise and placed a strain on government resources, so the patchiness of price reporting is unsurprising.
- Another consequence of the general lack of computing resources and personnel is that many of the data sets gathered (such as the price data set and some of the rainfall data) are archives that have not been kept up to date.
- Thirdly, in common with many other countries, the geographical units used to collect information vary between government ministries. Agricultural statistics tend to be available by communal area, for example, whereas health statistics are generally available by district. This makes the integration of different data sets more problematic, since boundaries of Communal Areas have to be overlaid on district boundaries.
- Fourthly, the geographical units used to collate several data sets (such as prices and livestock numbers) are difficult to locate on the map of Zimbabwe. This process, sometimes referred to as 'geo-coding' (Burrough, 1986: p. 179) is hampered by the

absence of standard numeric codes for the different parts of the country and by changes in the names and boundaries of administrative units on the map. This is particularly difficult in southern Africa, since many areas changed names after independence. This means that the names used on maps may differ from those used in tables of statistics, making the collation of information more laborious.

In addition, there are several features of the secondary data described here that are specific to Zimbabwe. One of these is the way that the pattern of land use affects data collection systems. For example, the LSCFA has a different method for reporting livestock numbers and crop production figures than the Communal Areas and this is a feature particular to Zimbabwe. A second, positive feature of organisations collating secondary data in Zimbabwe was their general willingness to share data sets. Spatial data sets were shared amongst a network of GIS users who met periodically to discuss key issues such as data exchange standards.

2.3 Collection of Primary & Secondary Data for Buhera District

2.3.1 Description of Buhera District

As noted earlier, more intensive secondary data collection, coupled with a questionnaire survey, also took place in Buhera District. Buhera District lies two hundred kilometres south of Harare in the province of Manicaland (see Map 2.2). It straddles the three least productive of the five agro-ecological zones of Zimbabwe. The southern part of Buhera falls under zone V where rainfall levels are low and the lands unproductive. The quality of land improves northwards so that the northern third of the district, falling under zone III, is generally food self-sufficient in aggregate. Buhera district comprises a former Tribal Trust Land, now known as the Save Communal Area. The district's main crops are maize, small grains (*mhunga*, *rapoko*, and sorghum), roundnuts (also known as bambara nuts), sunflower, and groundnuts. Most agriculture within the district is low-input and rain-fed, although there are two irrigation schemes: a smaller, older irrigation scheme in Murambinda in the north and a larger, expanding scheme near Birchenough Bridge in the south. As a traditional pattern of shifting cultivation has become increasingly intensive, much of the district is now covered by thorny scrub, although woodland still exists on rocky outcrops and near river beds (Campbell *et al.*, 1989). The area cultivated in the district has increased with its population and in some cases, land is now continuously cultivated. As

with many Communal Areas, the district's population is heavily reliant on money remitted by migrant labourers working outside the district on commercial farms, in the mining sector and in cities. Two tarmac roads skirt the district: one minor road across the north-western end (linking the GMB depot in Buhera town to the marketing network); the other, a more busy road, just crossing the southern most tip of the district. The interior of the District is served by a poorly maintained road system and there is no rail service.

2.3.2 Collation of Secondary Data for Buhera

An initial phase of secondary data collation took place prior to the questionnaire survey to assist with the sampling plan for the survey. Further details of the data sets collated are given in Table 2.5. I digitised all the map layers described below, using a combination of the Arc/Info, Atlas Draw, and AutoCad GIS systems (different packages were used in Harare and Edinburgh). Co-ordinates of points (such as health centres and water sources) were entered into the MapInfo GIS and converted to map layers using the 'create points' function. In all cases, spatial data were digitised in a Universal Transverse Mercator (Zone 36) projection and this was used as the common map projection for all subsequent work. The following information sets were computerised during this phase:

Location of Health Centres: As an indication of healthcare access, the locations of four types of health centre were available. These were full hospitals with facilities for performing operations; rural hospitals; clinics which had no operating facilities; and outreach centres, which were open irregularly and provided only basic services (immunisations, information dissemination, and health monitoring).

Roads and Topography: Contours and spot heights were available for the area and a current road map was obtained through the local government offices in the district.

Administrative boundaries: Boundaries were available for the main administrative units: wards, containing around 30,000 individuals, and Village Development Committees (VIDCO's) with populations typically around 5,000.

Water sources: A database of the locations and yields of water sources was also created, based on paper records held by local government. However, when the water sources were plotted out using a GIS, it became apparent that their accuracy was highly suspect. The co-ordinates for many water sources lay entirely outside the district, whilst others lay well outside the wards they were supposed to be contained by. When their locations were compared to place-names on paper maps of the district, it further became apparent that many place-names were inconsistent with locations. A short field reconnaissance with maps

plotted from the database co-ordinates showed many of the recorded water sources did not exist or were no longer functional. Consequently, this data set was not used in any subsequent analysis because of doubts about its quality.

Following the initial phase of secondary data collection, several other sources of data for Buhera were identified during the course of the next two years. Table 2.5 summarises the characteristics of data sets collected for Buhera during both these phases. In brief, information from the second phase included:

Irrigated areas: This showed the extent of the district's two irrigation schemes at Birchenough Bridge and Murambinda, as well as proposed future schemes.

Soils: This map used the standard soil classification for Zimbabwe (Nyamapfene, 1991). The district was mostly covered by fersiallitic soils, a widely cultivated soil group in Zimbabwe.

Smallstock: A smallstock survey that took place in September 1993 gave head counts of the number of sheep, goats, donkeys and pigs at dip-tanks across the district. However, since the names of many of the dip-tanks referred to could not be located on the available maps of Buhera, this data set was also not used in any subsequent analysis.

Settlement pattern: The 1:50,000 map series for Zimbabwe contains the locations of settlements across the district, though most of the maps in this series date from 1968. The following sheets were used to compile this map layer: 1931 A1, 1931 A2, 1931 A4, 1931 B1, 1931 B2, 1931 B3, 1931 B4, 1931 D1, 1931 D2, 1931 D4, 1932 A1, 1932 A3, 1932 C1, 1932 C2, 1932 C3, and 1932 C4. This data set is used in Chapter 7.

Locations of Business Centres: The District Administrator's office supplied grid references for 185 major settlements, which distinguished between Growth Points (large settlements), Rural Service Centres (medium-sized settlements), and Business Centres (smaller settlements) and was up-to-date. This data set is also used in Chapter 7.

Census data: Published 1992 census data are available for Buhera as district summary statistics only, except for counts of total population and numbers of households, which are available by ward (Government of Zimbabwe, 1993b). However, the IMFS project obtained permission to use ward-level summaries for other census variables within the district directly from the Central Statistical Office (CSO). The ward-level summaries supplied by CSO cover type of water source, sanitation, housing, migration, household head characteristics, and population structure by ward. These data are used in Chapter 7 with the permission of Mr. Parienyatwa of the CSO.

MUAC Survey: A cross-sectional anthropometric survey of young children included the number of children with Mid-Upper Arm Circumference (MUAC) in three different intervals was available for each ward. This was based on the results of an emergency village-based survey in 1992 designed to help target supplementary feeding of children.

Monthly health centre statistics: The IMFS project also gained permission to use the monthly health statistics returned through the National Health Information System for the district's health facilities. These were available from 1990, when the District Hospital at Murambinda first received a dedicated computer, until 1995. These statistics were obtained as a series of dBase files, though no attempt was made to access the paper archives of health centre records that extend back prior to 1990. The database included the number of reported cases of different types of disease, growth monitoring results, immunisations, natal healthcare provision, and contraception. The majority of health centres within the district consistently returned monthly statistics, although one health centre at Dandavare seldom managed to return any statistics. Several records were removed from this database where either the name of the health centre was left null or where the date entered was illogical. In addition, a check was made to ensure that the number of children underweight in the growth monitoring data was always less than the number of children weighed.

2.3.3 Sampling Strategy for Questionnaire Survey

In addition to the gathering of secondary data, a questionnaire survey of households was also undertaken in Buhera. An initial problem in implementing this survey was the identification of areas representative of the district in which to conduct the survey. As some secondary data had already been collected for the district, this provided a means of selecting areas for the survey. Since no information relating to under-nutrition prevalence *per se* was available at this juncture (although subsequently nutritional data were collated), information about the causes of poor nutritional status was instead used to select households to participate in the survey. Tagwareyi and Greiner (1994) have suggested that poor nutritional status in Zimbabwe is related to insufficient food access, poor health status, and inadequate care. Stratification to represent population characteristics related to these explanatory variables was required. Consequently, several secondary data sets were identified which could be related to these causes, were reasonably accurate, and were detailed enough to show variation within the district: the agro-ecological zones map, the location of health centres, roads and topography and administrative boundaries.

Data set	Temporal resolution / currency	Spatial resolution or scale	Collated by:	Responsible organisation
Health centres	1994	100 metre grid references	J Wright, P Mucavele, G Makombe, S Kudhlande, J Nyatsanza	Ministry of Health and Child Welfare
Road network	1994	1:250,000	J Wright, P Mucavele, G Makombe, S Kudhlande, J Nyatsanza	District Development Fund
Contours & spot heights		1:250,000	J Wright	Dept of the Surveyor-General
VIDCO & ward boundaries	1994	1:250,000	J Wright, P Mucavele, G Makombe, S Kudhlande, J Nyatsanza	Agritex, Mutare
Water sources	1994	100 metre grid references	J Wright, P Mucavele, G Makombe, S Kudhlande, J Nyatsanza	District Development Fund, Christian Care
Irrigation schemes	1994	1:250,000	J Wright	Agritex, Mutare
Soil types	unknown	1:250,000	J Wright, G Makombe, J Nyatsanza	Agritex, Mutare
Livestock numbers	One-time survey	Dip-tank	P Vaze, S Kudhlande	Department of Veterinary Services
Historical settlement pattern	1968	1:50,000	J Wright	Depart of the Surveyor-General
Current settlement pattern	1995	100 metre grid references	P Vaze, S Kudhlande	District Administrator's office
Census data	August 1992	Ward	P Mucavele, J Wright	Central Statistical Office
MUAC survey	One-time survey (1992)	Ward	S Gundry, Prof. A Ferro-Luzzi	Ministry of Health and Child Welfare
Monthly health statistics	Monthly	Health centre	P Mucavele, J Nyatsanza, J Wright	Ministry of Health and Child Welfare

Table 2.5: Characteristics of secondary data collected for Buhera District

These basic map layers were digitised and collated using a GIS. Factors affecting malnutrition appeared to operate at different geographical scales, so a hierarchical, stratified random sampling plan was adopted. In this sampling plan, large geographical areas were selected first and then smaller geographical sub-units were selected from within each of the larger selected areas. Table 2.6 outlines the structure of the sampling plan used. Stratification of larger geographical units (wards and VIDCO's) was performed using GIS, whilst smaller units (kraals) were stratified using rapid rural appraisal. I undertook the initial GIS work, whilst colleagues from the IMFS project (P. Mucavele, S. Kudhlande, J. Nyatsanza, and G. Makombe) performed the later stages of sampling.

Administrative Unit	Stratifying Variable	Method
Ward	Agro-Ecological Zone	GIS-Based
VIDCO	Access to Healthcare	GIS-Based
Kraal	Access to Potable Water	Rapid Rural Appraisal
Household	---	Random Selection

Table 2.6: Sampling Strategy for Household Selection

The largest units, wards, were selected on the basis of agro-ecological zone, since intra-ward variation in agro-ecological conditions could not be reliably assessed using the available data. The agro-ecological zone, which covered the greatest area within each ward, was calculated by overlaying the agro-ecological zone and ward maps using the GIS. Wards were then randomly selected from each zone in proportion to the total area of Buhera that lay within that zone. Ten wards were selected from a total of thirty within the district.

VIDCO's within the chosen wards were selected on the basis of access to healthcare. A 'pushbroom' method of calculating distance was used to assess healthcare access (Eastman *et al.*, 1989). This distance calculation method takes into account the effects of roads and obstacles such as hills or rivers, thereby providing a more realistic assessment of physical access. This procedure uses a 'difficulty of movement' map, which was created for Buhera on the basis of terrain and roads. Contours and spot heights were converted to a regular grid of elevation values by interpolation and slopes were calculated from this grid within the GIS. To incorporate the effects of roads, a panel of local government staff was invited to assess the ease of travelling along the different types of road in the district, compared to travelling across bush. The averages of their figures are shown in Table 2.7. The 'ease of movement' factor from this table was assigned to the respective types of road and the resultant map was then overlaid onto the map derived from slopes. This gave a map which represented 'difficulty of

movement', and this was then used to calculate distances to the four types of health centre (hospitals, rural hospitals, clinics, and outreach centres) using the 'pushbroom' algorithm.

Type of Road	Ease of Movement Relative to Bush	Factor
Tarmac	5 times easier	0.2
Primary, local government maintained/non-tarmac, central government maintained	3.3 times easier	0.3
Secondary, local government maintained	2.5 times easier	0.4
Tertiary, local government maintained	2 times easier	0.5

Table 2.7: Weighting Factors for Roads

The four separate distance maps were then combined into one composite healthcare access index. This involved three stages: firstly, standardising the distance maps so that each had broadly the same distribution of values; secondly, deciding on a set of weights reflecting the relative importance of the different types of facility; and thirdly, combining the maps using the set of weights. Standardising the distance maps prevented the map with the largest range of values from dominating the pattern of the final, composite map. This rescaling was achieved by subtracting the mean from each of the distance maps and then dividing by the standard deviation, having first checked that the distribution of distance values in each map layer was normal.

Next, a set of weights was developed so that the different map layers could be combined. Local Ministry of Health and Child Welfare staff in Buhera were asked to assess the importance of the different types of health centre for nutritional status. Each type of health centre was given a number that reflected its importance compared to an outreach centre. This procedure was adopted after experimentation with more complex ranking systems, such as Saaty's (1977) analytical hierarchy process, proved unsuccessful. A figure of 5 in this system thus implied services that were 5 times better than those of an outreach centre and a figure of 1 implied services equivalent to those of an outreach centre. Since opinion differed as to the relative importance of the different types of facility, several competing weighting systems were developed. The standardised distance maps were then multiplied by their respective weights and summed to give a composite index of access to health care. This was repeated for each of the competing weighting systems, to give several alternative maps of healthcare access.

After performing the map overlay, the different healthcare access maps were shown to Ministry of Health and Child Welfare staff for comments and feedback. The map which local

staff felt most accurately reflected access to healthcare in the district was based on the weightings shown in Table 2.8. Local staff also suggested the downgrading of two clinics to outreach centre status, one on the grounds that it had only recently been built, and a second on the grounds that it was only available to employees of a local mine.

Type of Facility	Rating for Services Offered (A)	No. of days services available / month (B)	final weight (A*B/30)
Hospital	7	30	7
Rural Hospital	5	30	5
Clinic	5	22	3.7
Outreach Centre	1	1	0.033

Table 2.8: Weighting Factors for Health Centres

The VIDCO boundary map was then overlaid on this preferred healthcare access map and the mean healthcare access index value for each VIDCO was calculated. VIDCO's were classified as having bad healthcare access if this value was worse than the average for Buhera and good if it was better than average. Map 2.3 shows the distribution of healthcare access by VIDCO used for stratification. One VIDCO with good access and one with bad access was then randomly chosen from within each of the selected wards, giving twenty selected VIDCO's in total. These selected VIDCO's, together with ward and agro-ecological zone boundaries, are shown in Map 2.4.

Having selected wards and VIDCO's, the final level of stratification at kraal level was performed on the basis of a rapid appraisal of water access. At this more localised level, the absence of suitably detailed secondary information precluded further use of GIS. Instead, the major types of water source used by each kraal were identified by survey and used to create an index of water access, again based on a weighting system developed in conjunction with local government staff. Three kraals were then selected from within each VIDCO on the basis of this water access index. Finally, 6 households within each of these selected kraals were chosen randomly to give a total of 354 households selected for the survey.

The selection procedure took some three months to implement, with approximately one month being devoted to the GIS-based stratification. Information from interviews and maps was combined together to produce the healthcare access index, and this index was verified through review by local people. This suggests both that the use of GIS for selection of areas for field study can be relatively quick, and that 'softer' information from interviews can be incorporated into a GIS-based methodology.

2.3.4 Questionnaire Survey Logistics

Patricia J Mucavele, G Makombe, P Vaze, A Conroy, J Nyatsanza, and S. Kudhlande designed a set of questionnaires to be administered to all selected households. I was involved in the critical review and revision of these questionnaires only. The three questionnaires used in this thesis (the Demographic Questionnaire, the Health Questionnaire, and the Assets and Income Questionnaire), largely designed by P J Mucavele, are included in Appendix 6. They cover four main areas: demography, the health environment (such as water source and sanitation type), household assets, and use of health facilities. The times of year when the different questionnaires were administered is shown below in Table 2.9.

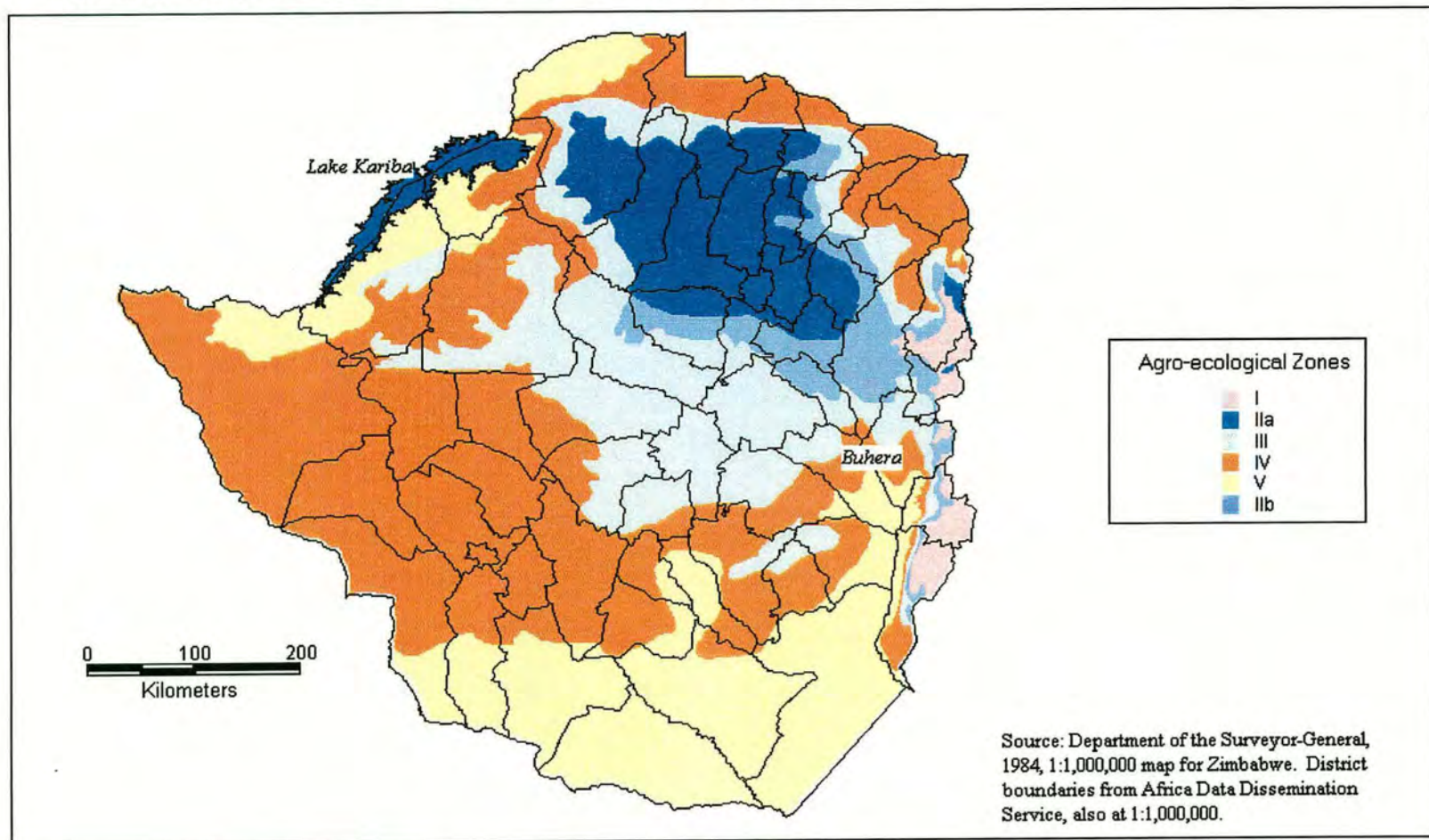
Questionnaire Name	Round	Month Administered
Demographic Assets & Income	1	Oct 94
Health Status	1	Nov 94
Health Status	2	Mar 95
Health Status	3	Jul 95
Demographic	2	Sep 95
Health Status	4	Nov 95

Table 2.9: *Timetable of administration for Buhera district household survey questionnaires*

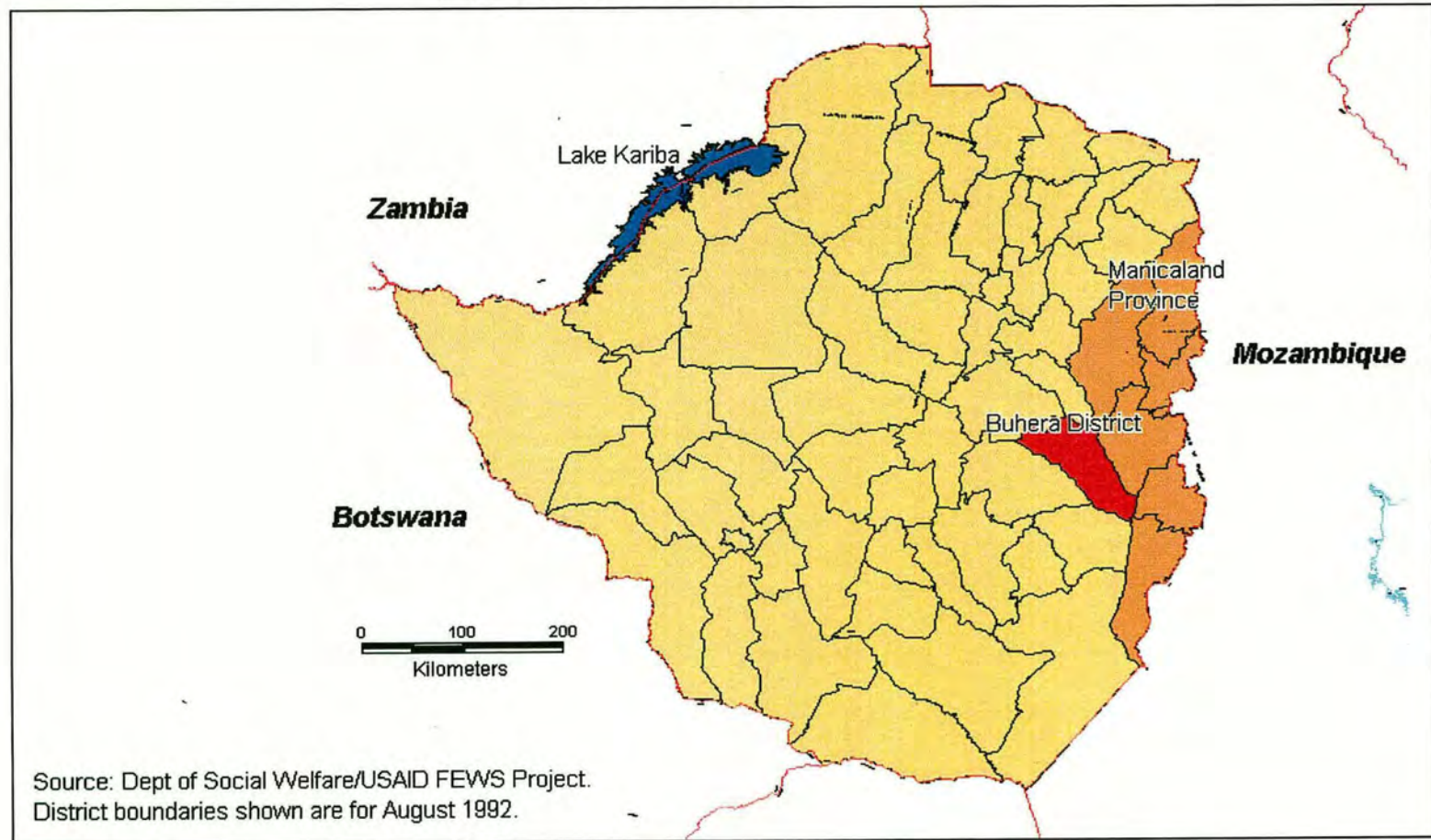
Enumerators for the questionnaire survey were selected and trained by Patricia Mucavele, G Makombe, and S Kudhlande, who also pre-tested the questionnaires. In total, ten local enumerators and a supervisor were hired to administer the questionnaires. The original questionnaires, which were in English, were translated into Shona prior to the interviews. I designed the database for the survey and data entry screens, and I supervised some of the data entry process. Logical checks were run on the information entered onto computer by P Mucavele, P Vaze, and myself. In addition to the questionnaire-based interviews, the location of the house of the headman of each *kraal* (village) was surveyed using a Global Positioning Systems receiver².

² The unit used was a Garmin GPS75, a non-differential GPS receiver accurate to approximately 30 metres.

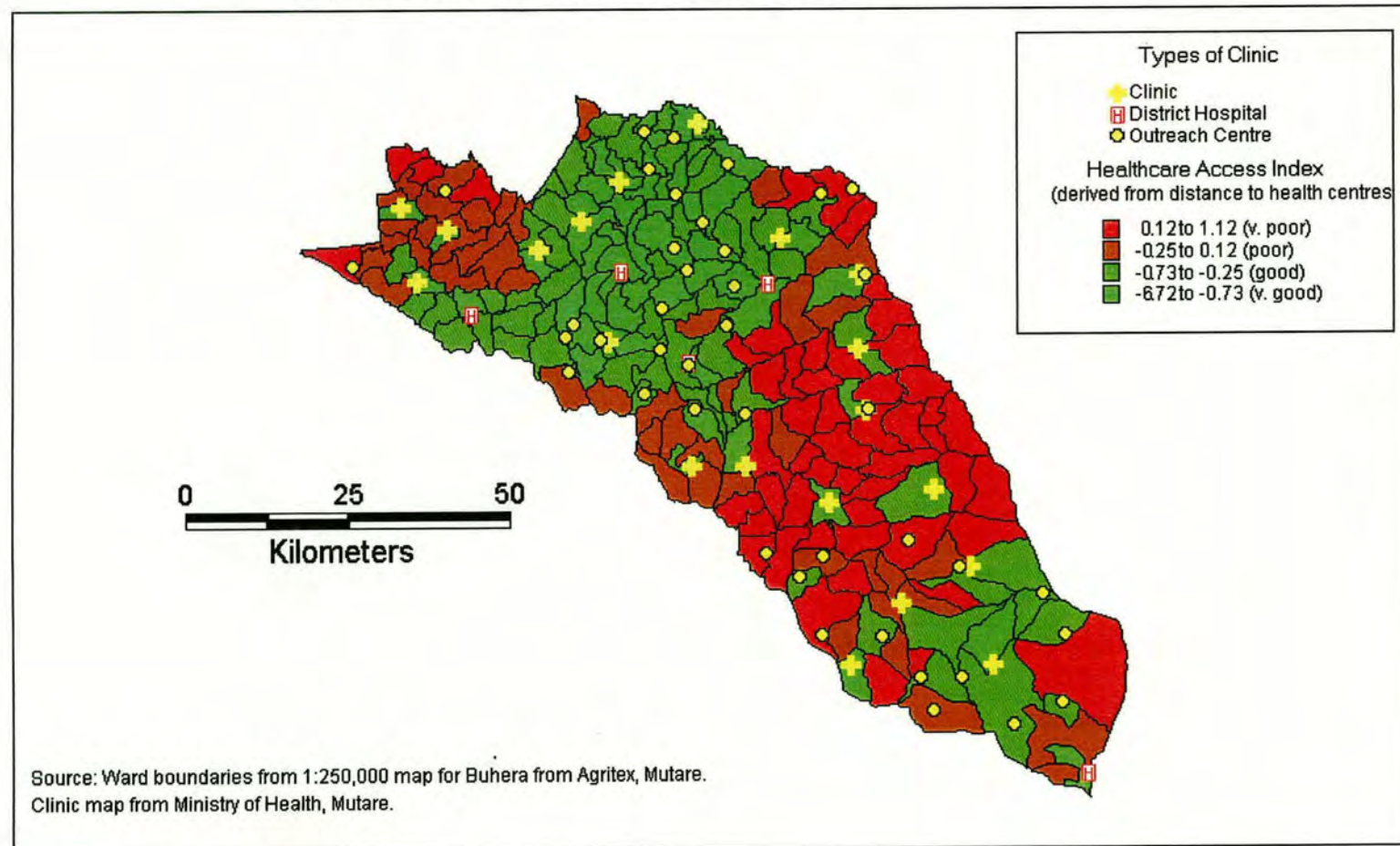
Map 2.1: Agro-ecological zones of Zimbabwe (see text for a description of each zone)



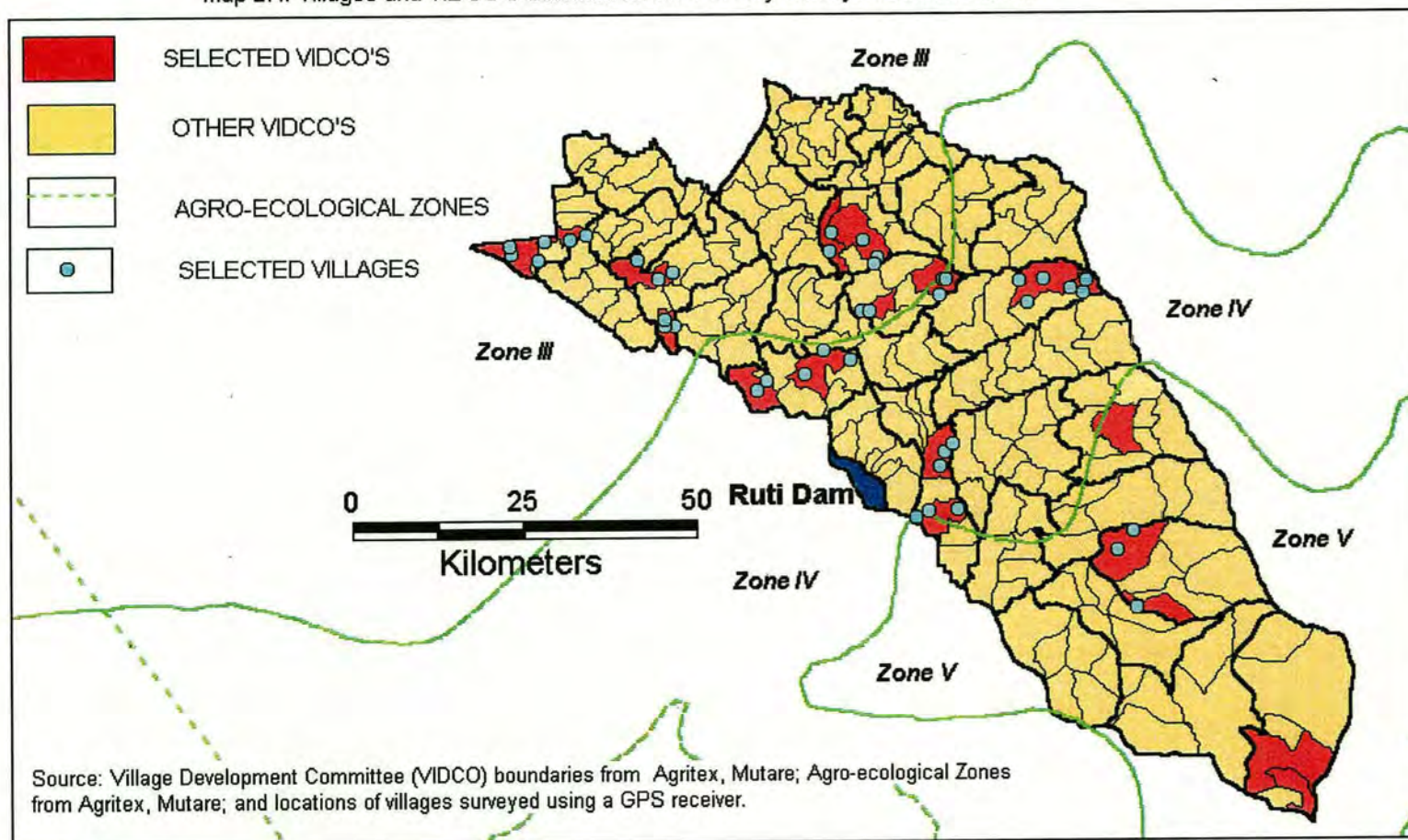
Map 2.2: Location of Buhera District



Map 2.3: Healthcare Access Index by Vidco for Buhera District



Map 2.4: Villages and VIDCO's Selected for the Primary Survey in Buhera District



3. ASSESSMENT OF ATTENDANCE AND BIAS

3.1 PARTICIPATION IN GROWTH MONITORING

3.1.1 *Introduction – Participation and Bias*

Thus far, we have seen that the National Health Information System (NHIS) provides the only comprehensive nutritional data set for Zimbabwe that is available both monthly and throughout the country. No other information-gathering programme has taken so many measurements over such a long, uninterrupted period of time. This NHIS operates in a similar way to information systems in other southern African countries, in that children are weighed when they visit health centres.

We have also seen that the main difficulty in interpreting the nutritional information gathered through the National Health Information System (NHIS) is that not all children are weighed. Some children do not visit health centres at all and are therefore not weighed, whilst others are infrequent visitors to health centres. Many of the factors that affect attendance at health centres, such as household income, remoteness of the household from facilities, and religious affiliation, may also affect the nutritional status of the child. For example, children in low income households are less likely to attend health centres (because of transport costs and health fees), and are more likely to be underweight. There is thus good reason to suspect that the NHIS may under-estimate the proportion of underweight children in Zimbabwe. Furthermore, the factors that prevent children attending health centres vary geographically, seasonally and over time. If attendance varies and this then biases the estimate of percentage under-nutrition, then comparison between different districts and different times becomes difficult.

This chapter investigates the question of bias in the NHIS information (thereby exploring Hypothesis B described in Section 1.4). After an initial discussion of healthcare demand and supply, patterns of attendance are examined geographically, seasonally, and inter-annually. Results are also examined from a 1994 survey, which measured children in their home communities, rather than at health centres. The proportion of underweight children in this survey is compared to the proportion estimated by the NHIS to see whether the two are different. The implications of this comparison for four policy uses of NHIS statistics are then discussed:

- for assessing national under-nutrition prevalence for making international comparisons;

- for assessing geographical variation in under-nutrition prevalence to target interventions at particular areas;
- for assessing trends in prevalence to identify the nutritional impact of policy or environmental changes;
- And for assessing seasonal variation in prevalence to time interventions within the year.

3.1.2 *Healthcare provision in Zimbabwe*

Many of the children who are weighed under the growth monitoring programme visit clinics to make use of other services, such as immunisation, treatment of illness, or as part of a visit by another family member. Attendance at growth monitoring is thus closely related to healthcare uptake, and this is affected by two categories of factor: healthcare provision (supply) and household characteristics (which affect demand).

Within Zimbabwe, six different types of healthcare provision can be identified. Aside from the state health system, private facilities also provide western-style healthcare, whilst traditional healers and religious healers offer alternative forms of healthcare. The use of ‘off-the-shelf’ medicines, as in many countries, is also common. Many Zimbabweans quite happily make use of several of these different types of healthcare, depending on their needs, and do not view them as mutually exclusive. Others (such as the Apostolic Faith, described below) rely exclusively on one type of healthcare only. These healthcare choices affect the information collected about under-nutrition by the NHIS, since weight measurements are only taken at state health centres and some private facilities. This means that the children of those choosing other types of healthcare may not be represented in the growth monitoring statistics on weight-for-age, and that these statistics may not reflect the prevalence of under-nutrition in the population as a whole. Each of these types of healthcare is discussed in greater depth below.

The main types of healthcare services are as follows:

- State health centres – As noted in the previous chapter, the state health service comprises four main levels of service. *Hospitals* generally have operating facilities and a doctor on the staff. *Rural hospitals* generally have a staff of several nurses, supplies of drugs, and beds available for patients. *Clinics* have a more limited supply of drugs and a smaller nursing staff. In addition, most communities are also serviced by *outreach centres*,

where a medical team visit once a month to perform immunisations, growth monitoring, and disseminate health information. Health facilities can also be classified according to their history, since as McCarty (1994) notes:

‘the mission hospitals in Zimbabwe are unique in that they are supported by the government. Before Zimbabwe's independence in 1980, all rural care was done by mission hospitals. When the country became independent, rather than build new hospitals, the government incorporated the mission hospitals into the government system and fully subsidised them.’

- Community health workers: In addition to these formal facilities, the state also provides paramedical community health workers. A village health worker programme was launched in November 1981, in which multipurpose community health workers were trained in preventive, promotive, and limited curative skills (Loewenson, 1991: p. 369). On commercial farms, a Farm Health Programme has been operating since 1994 that aims to strengthen the system of one Farm Health Worker on each commercial farm. One such worker, out of the 1,300 staff who have now been trained under the scheme, is quoted by Amanor-Wilks (1995: p. 30) describing her work:

‘the main problems I treat are diarrhoea, headaches, coughing, flu and malaria. Sometimes we get accidents..... I get drugs from the farmer's wife – flummel, aspirins, gingin violet and aqua flavin for burns. Month-end I go to Headlands to get bandages, burn creams, and panadol for the nursing and pregnant women who can't take aspirin. The clinic at Headlands supplies them free, if they're available.’

- Private doctors and clinics: A large private healthcare sector operates alongside the state-run facilities. These private facilities are particularly important in the wealthier urban areas. However, in Buhera we found a doctor operating a private practice in the northern, wealthier part of the district at Matimba between Murambinda and Buhera townships. His services were popular, despite the fact that he charged much higher fees than the state clinics and hospitals. Similarly, in north-eastern Buhera the Dorowa mining operation had a private clinic, which cared exclusively for miners and their families. Such private services are particularly important in the large-scale commercial farming sector, where the government provides tax incentives to farm owners to build private health facilities. This policy is preferred to the building of state facilities on commercial farms, which might indirectly increase the real estate value of the commercial farm, thereby subsidising the farm owner. Although some commercial farms have no private health facilities, in others health facilities are substantial. On the Triangle sugar estate in Chiredzi, for example, there is a privately funded, modern 150-bed hospital served by four doctors and a matching number of nurses (Amanor-Wilks, 1995: p. 20). Some of these facilities are integrated into the state health information

system, although others are not. For example, the miners' clinic at Dorowa in Buhera returns health statistics to the NHIS, whereas the private doctor's practice does not.

- 'off-the-shelf' medicines, provided by pharmacies are also used by the sick. Loewenson (1992: p. 111) noted that in a 1985 survey of healthcare use in Mashonaland West in a commercial farming area 'families commonly purchased medications from local stores, including tonics, diarrhoea remedies, cough mixtures, analgesics and anti-malarials'.
- Traditional healers (*n'angas*): A traditional Zimbabwean system of healthcare also operates alongside the western healthcare facilities described above. As Ncube (1997: p. 18) notes: 'Each village of between 700 and 1,500 families is served by two traditional healers'. Several types of traditional healer exist, specialising in midwifery, mental illness, and herbalism. The medicines used may include 'tree buck roots, leaves and plant bulbs, fish bones, shells, animal skins, porcupine quills, and rhino horn' (ibid). This traditional system enjoys official representation through the National Traditional Healers Association (ZINATHA), which certifies Spirit Mediums, who practice possession, and Traditional Medical Practitioners, who do not (Lan, 1983: p. 220). ZINATHA also has the power to expel *n'angas* who are seen as fraudulent or incompetent.
- Religious healers are also important healthcare providers for many Zimbabweans. Of particular importance is the Apostolic Church, which was founded by the prophet John Marange during the 1930s. The church now has a widespread membership in eastern Zimbabwe: we found 37% of our survey households in Buhera had at least some members who adhered to the faith, whilst in Dande, Lan (1983) found 8% of the population was Apostolic. As Lan (1983, p. 41) notes:

'They have their own rest days, their own meeting places, their own ways of curing diseases... In addition to their avoidance of "traditional" medicines and rituals, the Apostolics are also forbidden to use western-style medicines'.

3.1.3 *Healthcare funding in Zimbabwe*

Since 1991 healthcare funding, in common with many other forms of public expenditure, has been affected by public expenditure cutbacks. Table 3.1 shows that real expenditure on public healthcare fell from 47Z\$ to 32Z\$ between 1990-91 and 1993-94 and also fell as a proportion of GDP. Other authors (Watkins, 1995: p. 83; Bijlmakers *et al.*, 1996) have also reported this decline in real per capita health expenditure. To meet the decline in health funding from government, increasing emphasis is being placed on cost

recovery through user fees. Such fees were expected to recover a target of 5% of total healthcare expenditure by 1993 and 8% by 1995 (Gibbon, 1996).

	1988-89	1989-90	1990-91	1991-92	1992-93	1993-94
Share of GDP (%)	2.8	3.0	2.6	2.2	2.1	2.1
Expenditure per capita (Z\$ at 1990 prices)	46	49	47	41	33	32

Table 3.1: Expenditure on public healthcare, 1988-1994 (Reproduced from Gibbon [1996: p. 384]).

Until December 1991, healthcare was free to households with incomes below Z\$150/month, but fees had ceased to be collected even from households with incomes above this limit. In November 1992, a new exemption level of Z\$400/month was announced, but no mechanism for implementing it (Bijlmakers *et al.*, 1996). During this period, some 30,000 exemption letters were issued by the Department of Social Welfare, which covered medicines derived from hospital stocks but not from pharmacies. In January 1993, hospitals were told to waive fees but ‘in the interim, most hospitals had adopted their own systems for levying fees and determining exemptions. In January 1994, a new national fee system was introduced with substantial increases for some forms of treatment’ (Gibbon, 1996: p. 382).

Following resistance to the introduction of health fees, the charges were again withdrawn in 1995 (Watkins, 1995: p. 83).

The Buhera study also indicates that health fees were beginning to be introduced by rural facilities between 1994 and 1995. Over this period, four questionnaire surveys were conducted that examined use of healthcare facilities amongst 354 households over the preceding two weeks. Table 3.2 shows that some charges were levied throughout this period, but the proportion of patients charged for healthcare was greater during the early part of the survey. In many cases, those charged were in-patients, some of whom were hospitalised outside the district.

	Oct-Nov 94	Feb-Mar 95	Jun-Jul 95	Oct-Nov 95	All rounds
No visits	118	96	96	63	373
No charged	13 (11%)	9 (9%)	1 (1%)	1 (2%)	24 (6%)
Mean charge	6Z\$	7Z\$	14Z\$	15Z\$	7Z\$
Total charged	76 Z\$	63 Z\$	14 Z\$	15 Z\$	168 Z\$

Table 3.2: Charges levied at state health centres in Buhera district between 1994 and 1995.

Although the proportion of patients charged fees in Buhera was relatively small, the fact that fees were charged at all may still have discouraged local households from bringing their children to be measured at health facilities.

3.1.4 *Household characteristics and healthcare uptake*

Clearly, healthcare uptake is also affected by the characteristics of the households living within a given area. In the case of the state health centres, one of the more obvious characteristics affecting attendance is remoteness. There is an opportunity cost in time for more distant households attending health services and there may also be financial costs in terms of transport fees. Income and wealth are important in that some households have assets such as Scotch carts making transport easier, whilst high-income households can clearly afford transport costs and health fees. The interaction between remoteness, income levels, and available time is illustrated by Loewenson's (1992: p.112) observations concerning healthcare uptake in commercial farming areas: in the early part of the year, 'over-the-counter drug purchases were used to save on lost work time. In the later part of the year, when cash demands for food, school fees, and other household requirements increase and with a slightly lower peak in female employment, greater use was made of free state facilities.'

As noted previously, households also make use of alternative forms of healthcare for cultural and religious reasons. The use of religious healers amongst the Apostolic Faith is particularly important, since faith members do not use formal health facilities as a tenet of their religion. In contrast, those using traditional healers (*n'angas*) often switch between western-style healthcare and traditional health services depending on the nature of the problem experienced.

3.2 PATTERNS OF ATTENDANCE

3.2.1 *Trends in growth monitoring attendance*

The NHIS collects information on the number of children weighed, as well as the proportion of children suffering from weight-for-age malnutrition. This means that the trends in attendance at the growth monitoring programme can be assessed, which provides one means of assessing the impact of the introduction of health fees discussed earlier.

In order to assess the proportion of children under 5 years being weighed under the growth monitoring scheme, the size of the total population under 5 years needs to be estimated from census data. Between the 1982 and the latest 1992 census, administrative boundaries underwent considerable revision as the pre-independence system of government was restructured. Since even Zimbabwe's provincial boundaries changed, this makes it almost impossible to estimate the rate of population growth at a sub-national level. Consequently, trends in growth monitoring attendance are assessed here at a national rather than provincial or district level. The Zimbabwean 1992 demographic census and the 1987 inter-censal surveys indicate that the average annual percentage increase in children under 5 years over this period was 2.04%, lower than growth in the population as a whole (Government of Zimbabwe, 1991; Government of Zimbabwe, 1994e). This linear percentage increase for the period 1987-1992 was applied to the period of the NHIS data (1988-1995) to estimate the change in the under-5 population from the time of the 1992 census onwards.

Year	Total population	Cohort aged 0-4 years	Percentage of total aged 0-4 years
1969 ¹	5099314	1039750	20.4
1982 ¹	7608432	1327340	17.4
1987 ²	8689000	1437713	16.5
1992 ³	10412548	1584691	15.2

Table 3.3: *Changes in the Zimbabwean population under 5 years between 1969 and 1992* (Sources: ¹ Government of Zimbabwe [1985]; ² Government of Zimbabwe [1991]; ³ Government of Zimbabwe [1994e])

The total number of children participating in the growth monitoring programme nationally for each month was calculated by aggregating the district totals for the period 1988 to 1995. Where a district did not return any statistics for a particular month, total attendance was estimated using the average of the previous and following months' attendance figures. The results of this exercise, expressed as a percentage of the total population under 5 years, are shown in Figure 3.1. Two features of the patterns of attendance are apparent: firstly, attendance can fluctuate sharply from one month to the next. Secondly, attendance rose quickly during 1988 and early 1989 and then increased slightly until 1992. After 1992, the proportion of children attending the scheme fell slightly. Over the whole period, the proportion of children participating in the scheme every month is estimated to have varied from 17.4% to 27.5%.

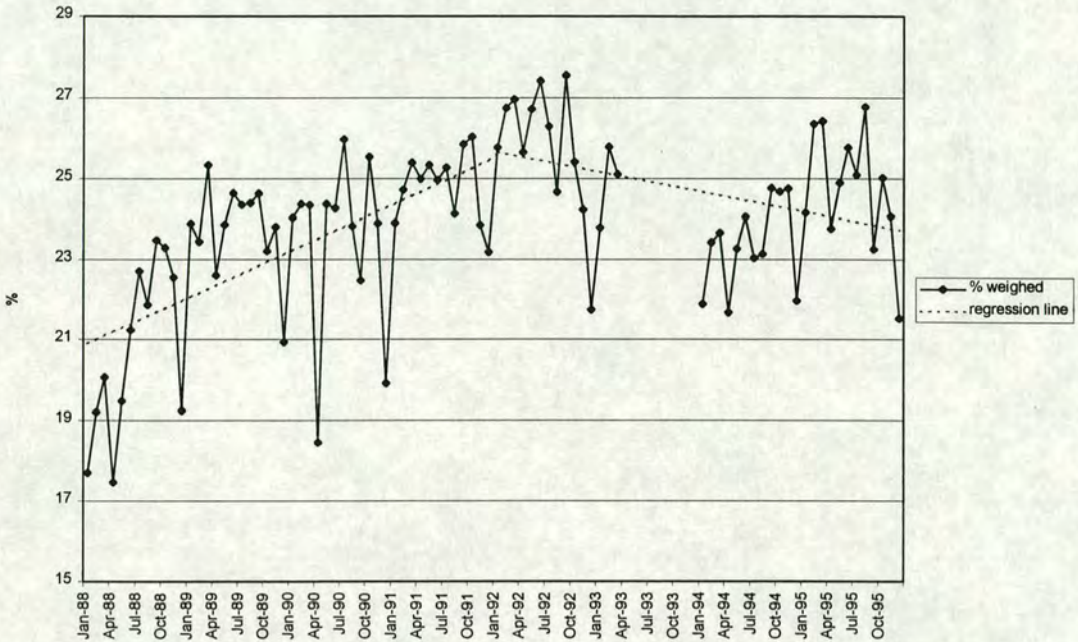


Figure 3.1: *Proportion of children weighed under the growth monitoring programme between January 1988 and December 1995* [Source: National Health Information System, Government of Zimbabwe (1991); Government of Zimbabwe (1994e)]

This visual inspection of the change in attendance with time can be corroborated using regression analysis. A test was made to see whether the form of a linear regression equation during the period before health fees were introduced was different from the form of a linear regression equation thereafter. For this purpose, January 1992 was taken as the month when health fees were introduced, following Gibbon's (1996) description of changes under the Economic and Structural Adjustment Programme (ESAP). The form of this regression equation was as follows:

$$Y_t = b_0 * t + b_1 * x_t + b_2 * t * x_t + c$$

...where Y_t is the attendance level at growth monitoring in month t , x_t takes a value of one when health fees were being charged and zero at all other times, c is a constant, and t is time in months. This equation tests for a change of slope in the regression equation as well as a change in the constant term following the introduction of health fees.

Regression results for this equation are shown in Table 3.4 and the fitted line is plotted in Figure 3.1 above. All terms in the regression equation were significant, suggesting that ESAP may have influenced attendance at growth monitoring. The regression model, which was based on 86 months' data, had an adjusted R^2 of 0.36. This gave a better fit than a simple linear model, which ignored the impact of ESAP on attendance (such a model had an adjusted R^2 of 0.15) and a similar fit to a quadratic model (which also had an adjusted R^2 of 0.36). The coefficients in Table 3.4 suggest that the percentage of children attending growth monitoring was initially around 21% and then rose at a rate of 0.1% per month until the beginning of 1992. Following this point, attendance declined at a rate of 0.14%.

<i>Variable</i>	<i>Coefficients</i>
Intercept (c)	20.81 (**)
Time (b_0)	0.10 (**)
Change of slope under ESAP (b_2)	-0.14 (**)
Change of constant under ESAP (b_1)	6.85 (**)

Table 3.4: *growth monitoring participation regression model results, testing for a change in attendance patterns after health fees* (based on 86 months' data, with the model having an adjusted R^2 of 0.36).

Although these results apparently suggest that a decline in attendance came about as a result of ESAP, the decline in real health expenditure, and the introduction of health fees, they do not provide conclusive proof. The choice of January 1992 as the break between the two fitted lines is subjective. Clearly, splitting the time series at a different point may produce a better explanation of attendance patterns. Such a point may represent some other influence on attendance apart from the introduction of health fees, such as the onset of the 1991/92 drought. However, further evidence on the impact of health expenditure on attendance can be derived from more detailed attendance records at different types of facility for Buhera district.

3.2.2 *Attendance at different types of facility*

The decline in real per capita healthcare expenditure is likely to have reduced the scale of outreach operations by decreasing the provision of transport and availability of diesel. This potential impact on attendance can be investigated by assessing the trends in growth monitoring attendance at outreach centres compared to permanent facilities.

Detailed growth monitoring records had been collated for Buhera district for the period 1991 to 1995, which break down attendance by health centre. These records enable the attendance trends in growth monitoring undertaken by mobile outreach centres to be compared with attendance at permanent health facilities. Unfortunately, the usefulness of Buhera district for analysing the share of attendance at outreach centres is reduced by the fact that a new clinic, Chapanduka, began conducting growth monitoring in February 1994. This is likely to have increased attendance at growth monitoring at permanent facilities, but decreased attendance at growth monitoring conducted by the outreach teams. Analysis of this information was further complicated by the fact that statistics were unavailable for certain health facilities in some months. This problem was dealt with using two methods. Using the first method, it was assumed that the health facility had not measured any children during that month and consequently, the number of children weighed was assumed to be zero. In the second scenario, it was assumed that the health facility had continued to operate normally but had failed to complete the necessary tally form for that month. In this scenario, any months with missing data were replaced with the moving mean of the two adjacent months.

Figure 3.2 shows the change in attendance at growth monitoring in outreach centres compared to permanent facilities under these two scenarios. In both cases, outreach centre attendance increases until August 1992 and then declined thereafter. Attendance at permanent health facilities shows a slight rise over the period available.

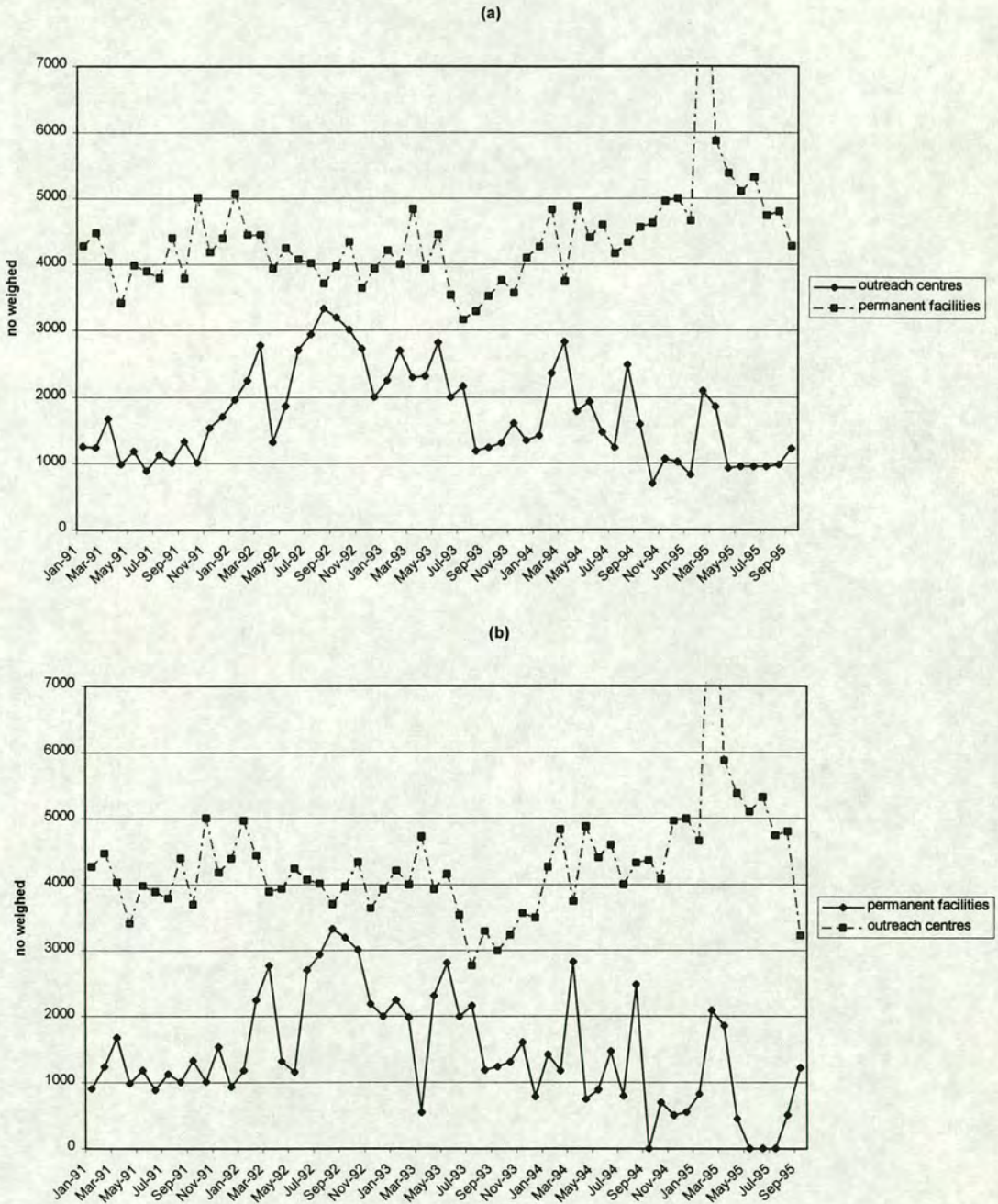


Figure 3.2 (a): Growth monitoring attendance at permanent health facilities and outreach centres in Buhera district from 1991-1995, replacing 'missing' values with moving averages. **(b)** Growth monitoring attendance at permanent health facilities and outreach centres in Buhera district from 1991-1995, replacing 'missing' values with zeros.

3.2.3 *Seasonal variation in growth monitoring attendance*

A test was also made for a seasonal pattern in attendance at growth monitoring. Four dummy variables were created, each representing one quarter of the year (January-March, April-June, July-September, or October-December). Each of these variables took a value of 1 during the season concerned and a value of zero at all other times of the year. Following Gujarati's (1988) method for identifying seasonal variations in time series data, these four seasonal dummy variables were entered into a stepwise regression equation predicting total attendance at growth monitoring. It was found that none of the seasonal dummy variables were associated with the variation in attendance at the scheme, and all had insignificant *T* statistics. Thus, differences in attendance between quarters were statistically insignificant ($P = 0.05$).

3.2.4 *Geographical variation in growth monitoring attendance*

A 'snapshot' of attendance at growth monitoring can also be obtained by comparing the figures for attendance from the NHIS with the number of children under 5 years recorded in the 1992 census. The census distinguishes between infants less than 1 year old and children between 1 and 4 years old, a distinction that is also used in the NHIS data set. This means that the two data sets are directly comparable for the month of the census, August 1992.

Nationally (excluding Umguza district for which data are missing), the proportion of infants being weighed was 50.4%. This was much higher than the proportion of older children being weighed, which stood at only 17.5%. Both figures may be a slight over-estimate of the number of children being weighed, since they ignore the possibility that children may be weighed twice in the same month.

Map 3.1 shows the percentage of infants under 1 year being weighed under the growth monitoring programme in August 1992, whilst Map 3.2 shows the percentage of children aged 1-4 years weighed in the same month. The proportion of infants being weighed is highest in the more urbanised parts of Zimbabwe, whilst the areas with low attendance tend to be in the communal lands, located in the drier parts of Zimbabwe. Attendance is higher in central Mashonaland and Manicaland and lower in the provinces of Masvingo and Matabeleland South.

3.3 COMPARISON WITH A COMMUNITY-BASED ANTHROPOMETRIC SURVEY

3.3.1 *Comparison of underweight prevalence in DHS and NHIS*

A second means of assessing the impact of variable attendance on the under-nutrition prevalence estimated by the growth monitoring programme is to compare this estimate to the results of a community-based survey. One such set of surveys carried out in children's communities rather than at health centres, is the Demographic and Health Surveys (DHS) that were funded by the US Agency for International Development (Macro International, 1990; Macro International, 1995). The DHS III survey of Zimbabwe, which took place between July and November 1994, is available over the Internet and is used here¹. Elsewhere, DHS data have been used to examine the accuracy of vaccination rates reported by WHO and UNICEF (Eblen et al, 1998), though no study has compared growth monitoring and DHS data in any depth. In Zimbabwe, DHS data have been used to assess patterns of child mortality (McMurray, 1997) and the causes of child under-nutrition (Madzingira, 1995).

Anthropometric measurements were taken as part of DHS III for most of the children aged under 36 months of the 6,128 women involved in the survey. As well as anthropometric indices (weight-for-age, height-for-age, and weight-for-height), the original age, height, and weight data are available for all the children measured, so this gives flexibility in defining age cohorts and applying anthropometric standards. The standard used in the NHIS (the third percentile of the NCHS/WHO population) can therefore be used to define the cut-off point for weight-for-age in the DHS data. The NHIS distinguishes four age categories (under 6 months, 6-11 months, 12-23 months, and 24-59 months), so a comparison of the two data sets is only possible for the youngest three age cohorts. This can be achieved by excluding all of the children weighed under the DHS aged 24 months or older.

The mean percentage malnourished nationally was calculated using NHIS data for the same period as the DHS (i.e. July to November 1994). Where a district did not return statistics for a given month, this was replaced with the moving mean of the previous and

following months' statistics. This gave an estimated underweight prevalence of 5.64% amongst children under 2 years nationally, as shown in Table 3.5.

Even though the DHS is a community rather than clinic-based survey, there is still potential for bias, since not all selected children could be weighed. Out of the 1431 children aged less than 24 months, 57 (4%) were not weighed as part of the DHS. Of these, 41 children were not present and therefore could not be weighed, although the families of 5 children refused to allow them to be weighed (in other cases, no explanation was given as to why a child was not weighed). If these children are more likely to be under-nourished, then the DHS itself could slightly under-estimate the prevalence of nutritional problems.

In practice, four different estimates of the prevalence of under-nutrition can be derived from the DHS data, depending on how problems of sampling intensity and outlying data points are treated. To achieve large enough samples for compiling provincial statistics, the DHS sampled certain parts of Zimbabwe more intensively than others. Consequently, the sample is weighted, so that children measured in certain parts of the country carry more importance statistically than those measured in other places. Furthermore, the raw survey results also include certain outliers, which could be excluded from any estimate of the total under-nutrition rate. These outliers occur where age information is inconsistent with the corresponding weight and height measurements and were identified using the anthropometric indices (height-for-age, weight-for-height, and weight-for-age). This gives four possible estimates of under-nutrition prevalence: unweighted, with no exclusion of outliers (1); weighted, with no exclusion of outliers (2); unweighted and excluding outliers (3); or weighted and excluding outliers (4). It is argued here that whilst option (4) would give the most accurate estimate of under-nutrition prevalence, option (2) would give a prevalence figure that most closely resembles that derived from the NHIS. This is because no attempt is made to identify outlying values of weight-for-age within the NHIS (once a child leaves with the health card, then this is no longer possible). The two options that ignore the sample weights (1 and 3) are unlikely to provide an accurate estimate of the national prevalence of underweight children.

¹ The results of the first DHS survey, which took place in Zimbabwe in 1988, had also recently been made available over the Internet at the time of submission. Analysis of 1988 DHS data would form a valuable addition to this chapter.

Data source	Total sample size	Total under-weight	Estimated Prevalence of Under-Nutrition
NHIS T5 summary sheets	1365671	77075	5.64%
DHS, with no weighting of observations or removal of outliers (1)	1431	102	7.13% (**)
DHS, with weighting of observations and no removal of outliers (2)	1482	98	6.58% (**)
DHS, with no weighting of observations and removal of outliers (3)	1393	95	6.82% (**)
DHS with weighting of observations and removal of outliers (4)	1434	90	6.26% (**)

Table 3.5: National estimates of under-nutrition prevalence in children under 2 years for July-November 1994 (based on 3rd percentile of weight-for-age; ** indicates that the proportion under-nourished is significantly different from the NHIS estimate at the 99% level).

Sampling theory enables DHS estimates of percentage under-nutrition which are significantly different from NHIS estimates to be identified. The standard error of the difference between two proportions derived from different samples can be given by:

$$\sigma_{(p_1 - p_2)} = \sqrt{(p.q/n_1 + p.q/n_2)} \quad (3.1)$$

where p = pooled proportion under-nourished, $q = 1 - p$, n_1 = size of first sample, and n_2 = size of second sample (Harper, 1982: p. 184). Applying this to the two samples here, the percentage of under-weight children is significantly higher in the DHS sample for all four of the calculation methods (1-4) described above, as shown in Table 3.5.

3.3.2 Comparison of DHS and NHIS by province

The DHS survey results can also be broken down by province and compared to the results from the NHIS. This indicates how far the NHIS can be used for targeting areas with a high prevalence of under-nutrition. Following the methodology adopted by Pelletier and Johnson (1994), this geographical comparison was made in two stages. Firstly, a test was made for significant differences between the NHIS and DHS under-nutrition prevalence estimates for each province. The results of this exercise are shown in Table 3.6. The DHS estimates of the percentage of underweight children under 2 years old were not significantly different from any of the NHIS estimates.

Province	NHIS % underweight	No. children weighed (NHIS)	DHS - % underweight	No. children weighed (DHS)
Bulawayo	2.92	80567	3 (n.s.)	100
Mash. East	6.14	138972	2.88 (n.s.)	139
Harare	2.88	283344	4.5 (n.s.)	111
Midlands	6.12	152849	4.52 (n.s.)	177
Masvingo	4.7	149614	6.56 (n.s.)	122
Manicaland	6.1	181673	8 (n.s.)	125
Mash. Central	7.06	99868	8.76 (n.s.)	137
Mash. West	5.94	137246	9.62 (n.s.)	156
Mat. North	8.74	65815	9.79 (n.s.)	221
Mat. South	12.71	75724	10.41 (n.s.)	143

Table 3.6: Comparison of provincial underweight prevalence in children under 2 years old for Demographic and Health Survey versus National Health Information System for 1994 (DHS data have no weights or removal of outliers; n.s. indicates that the DHS estimate was not significantly different from the NHIS estimate).

Secondly, the correlation co-efficient of the two different sets of estimates of provincial underweight prevalence was calculated. The two sets of estimates were found to be significantly correlated ($R=0.708$, $N=10$). In both the NHIS and DHS data, Matabeleland North and Matabeleland South were the provinces with the highest proportions of underweight children, whilst Harare and Bulawayo were amongst the three provinces with the lowest proportions.

3.3.3 age prevalence characteristics

The difference between the NHIS and DHS estimates of the percentage of underweight children can also be assessed for the different age cohorts. Table 3.7 indicates the differences between the three sets of estimates for children below 6 months, 6-11 months old, and 12-23 months old. The estimates derived from DHS take account of the sample weighting, but outlying values of the weight-for-age Z-score have not been removed in their calculation (the estimates are therefore based on method 2 described in section 3.3.1). Applying equation (3.1) to these cohort estimates of prevalence suggests that the NHIS figures over-estimate the percentage of underweight in the youngest age cohort, but under-estimate underweight prevalence in the 12-23 month age cohort.

Age cohort	No children (DHS)	No children (NHIS)	Percentage underweight (DHS)	Percentage underweight (NHIS)
0-5 months	358	325,494	0.60	2.53 (*)
6-11 months	407	541,044	2.87	3.94 (n.s.)
12-23 months	666	500,066	12.06	9.52 (*)

Table 3.7: Comparison of national underweight prevalence in children under 2 years old for Demographic and Health Survey versus National Health Information System for 1994, broken down by age cohort (* indicates estimated prevalence significantly different at the 95% level; n.s. indicates estimated prevalence not significantly different)

3.3.4 Relationship between Health Card Possession and Under-Nutrition

Aside from assessing bias by comparing the prevalence of under-nutrition in the DHS data with the prevalence found in the T5 data, possible bias can also be identified by looking at the DHS sample in isolation. The DHS survey records whether or not a child possesses a health card. This means that a test can be made to see whether those with health cards are different in terms of their nutritional status from those without health cards. Table 3.8 shows the nutritional status of children cross-tabulated against possession of a health card. A chi-square test on the raw, unweighted numbers of children falling in each cell in this table suggested that there was no significant difference in nutritional status between card-holders and those without cards. Similarly, a chi square test applied to the weighted numbers of children also suggested that there were no significant differences in nutritional status between card-holders and non-card holders ($df=3$, $p=0.95$).

	Healthy	Under-nourished	total
Child has no card	64	6	70
Child has card & card seen by interviewer	1582	170	1752
Card has card but card not seen by interviewer	227	27	254
Child no longer has card	33	6	39
Total	1906	209	2115

Table 3.8: Possession of health cards and nutritional status of children under 36 months in the DHS survey (children are listed as undernourished if their weight-for-age is less than the 3rd percentile of the standard population used in the NHIS. Sample weights have not been applied to the data)

3.4 DISCUSSION

3.4.1 *Implications for assessing national prevalence*

The analysis of growth monitoring uptake suggested that attendance varied both geographically and by age group. The latter accords with the findings of an earlier study (Government of Zimbabwe, 1992), who found that children were weighed six times on average in the first year of life, four times in the second year, and that the number of weighings declined thereafter. This pattern of attendance, which illustrates the close relationship between immunisations and growth monitoring, means that young children are over-represented and older children under-represented in growth monitoring statistics. Because underweight prevalence is higher amongst older children (Tagwireyi and Greiner, 1994), this is likely to produce an under-estimate of national prevalence. The geographical variability in attendance has much the same effect. Fewer children in rural areas, where underweight prevalence is generally higher, attend growth monitoring compared to urban areas and this is again likely to lead to an under-estimate of national prevalence.

These findings accord with comments made elsewhere concerning prevalence data (Marterell, 1993: p.244): 'In making comparisons of prevalence, whether among countries or across time, attention needs to be paid to the age composition of the sample'. One way of correcting for the differing levels of attendance between different age cohorts might be to give more weight to measurements of children in age groups where attendance is low. Similarly, less weight could be given to children in age groups where attendance is high. One such weighting system would be as follows:

$$\text{Adjusted under-nutrition rate} = \sum_{i=1..n} R_i * PP_i / PS_i \quad [3.2]$$

(for a sample of i population sub-groups, where R_i is the under-nutrition rate in sub-group i , PP_i is the proportion of the total population in sub-group i , and PS_i is the proportion of the sample population in sub-group i .)

In the case of Zimbabwe, the proportion of children in the 0-5, 6-11, and 12-23 month age cohorts is not available through the census. However, assuming negligible mortality and changes in the number of live births, 25% of children under 2 years would be in the first category, 25% in the second, and 50% in the third. These figures can be applied to the equation above to estimate a national under-nutrition rate of 6.05%. This is still

significantly different from the DHS figure of 6.58% at the 95% level, but is much closer than the original, unweighted estimate from the NHIS.

However, the weighting system can be further improved by compensating for the differing levels of attendance between provinces, as well as between age cohorts. Thus, children from provinces with low attendance are given more weight than children from provinces with high attendance. If equation [3.2] is applied to the NHIS data again, but this time using weighting factors both for province and for age cohort, then the estimated national prevalence rises to 6.74%. This is not significantly different from the DHS estimate of 6.56%, suggesting that such a weighting scheme may help reduce bias in such clinic-based data in this case. Although clinic-based statistics are not generally used for making international comparisons (de Onis *et al.*, 1993), such a weighting scheme would enhance the value of NHIS data for this purpose.

3.4.2 Implications for comparing prevalence between provinces and age groups

The geographical variability in growth monitoring attendance suggests that comparison of prevalence in different areas may be misleading, if those who are not weighed differ from those who participate. However, the DHS and NHIS provincial estimates of underweight prevalence were well correlated. Both data sets showed the urban provinces as having low underweight prevalence, whilst the rural provinces of Matabeleland North and Matabeleland South in western Zimbabwe had some of the highest prevalence rates. This suggests that the growth monitoring scheme is still useful for targeting at provincial level.

Comparison of NHIS statistics with the Demographic and Health Survey of 1994 provides further insights into assessing prevalence differences between age cohorts. When the three main age cohorts of young children were compared, it was found that the NHIS actually over-estimated under-nutrition prevalence in the 0-5 month age bracket. The NHIS estimate for the 6-11 month age bracket did not differ significantly from the DHS, whilst the NHIS under-estimated under-nutrition in the 12-23 month age bracket. Perhaps surprisingly given these results, there was no difference in nutritional status between children who possessed health cards and those who did not. One possible interpretation of these results is that the bias problem results not from differences between growth monitoring participants

and those who stay away, but in differences in frequency of attendance among the participants. It would appear that the frequent attendees in the first six months of life are more likely to be under-nourished, whilst frequent attendees between 12-23 months are less likely to be under-nourished. These discrepancies within cohorts between the two data sets also explain why the weighting system above is unable to eliminate bias from the NHIS entirely.

3.4.3 *Implications for assessing trends in prevalence*

The assessment of the suitability of NHIS data for trend analysis ideally requires two comparisons to be made with independent data sets – one comparison when the scheme was introduced and a second comparison more recently. In fact, previous work (UN ACC-SCN, 1992) has compared national underweight prevalence in the NHIS with that in an earlier Demographic and Health Survey in Zimbabwe, which took place in 1988. The NHIS indicated that 11.4% of children under 5 years were below the third percentile for weight-for-age, whilst the 1988 DHS survey indicated that 11.5% of under-fives were below the 2.3 percentile for weight-for-age. The second 1994 DHS data used here suggested that 6.82% of children under 2 years were below the third percentile of weight-for-age, whilst the NHIS suggested that 5.64% of children under two years were underweight by the same criterion. Both the 1988 and 1994 comparisons suggest that the growth monitoring scheme slightly underestimated underweight prevalence amongst young children. However, given different age cohorts of children were assessed in the two DHS surveys, it is difficult to interpret the implications of this finding for analysing trends in the growth monitoring data.

An alternative approach, therefore, is to examine changing patterns of attendance over time. Such an analysis suggests that during the early years of the programme, the government was successful in increasing participation in the scheme, perhaps partly because of the increases in real expenditure on healthcare funding that took place at that time. Secondly, there is evidence that the number of children attending growth monitoring has declined slightly since 1992. This slight decline may be because the reduction in per capita health expenditure may have placed a strain on the growth monitoring programme. It is conceivable, for example, that problems of maintaining vehicles may have reduced the activities of outreach teams, who are important in remote areas. However, the slight decline

may equally well be related to the introduction of health fees or to other contemporary changes such as the severe drought of 1991/92.

The broadly similar percentages of children attending growth monitoring from mid-1989 through to 1995 suggests that cut-backs in healthcare expenditure and the introduction of health fees have not led to drastic reductions in growth monitoring attendance. The similar results obtained in comparing 1988 and 1994 DHS data with growth monitoring estimates of prevalence also suggest trend analysis of NHIS data may be valid, but should be treated with caution because of the change in the ages of children measured under the DHS. These results suggest that trend analysis of NHIS data may be valid, but are far from conclusive.

3.4.4 *Implications for assessing seasonal variation in prevalence*

The regression-based test for seasonal variability in growth monitoring attendance suggested that there were no significant differences between different quarters of the year at national level. This implies that the growth monitoring data can reliably be used to compare prevalence between seasons.

3.4.5 *Comparison with findings from other countries*

As noted in Chapter 1, growth monitoring schemes that weigh children in clinics exist in many other countries apart from Zimbabwe. Table 3.9 summarises findings in the literature about other such schemes around the world. Findings vary from country to country, depending on the detailed implementation of the monitoring system. At national level, for example, the El Salvador monitoring system over-estimated under-nutrition because a large number of sick children were weighed as part of the scheme. In contrast, the Malawian scheme under-estimated the prevalence of underweight children because it was based on measurements taken at Well Child Clinics of healthy children (Pelletier and Johnson, 1994). The Zimbabwean system, based predominantly on children seeking immunisation, falls somewhere between these two cases. At the sub-national level, the results presented here accord with findings in Botswana and El Salvador, but contrast with

those of Serdula *et al.* (1987) and Pelletier and Johnson (1994) in Swaziland and Malawi respectively.

Country	Reference	National	Sub-national	By clinic
Botswana	UNICEF (1983)	Comparable	Correlated ²	
El Salvador	Trowbridge <i>et al.</i> (1980)	Over-estimate	Correlated	
Jamaica	Grosh <i>et al.</i> (1990)	Comparable		
Malawi	Pelletier and Johnson (1994)	Under-estimate		No correlation
Swaziland	Serdula <i>et al.</i> (1987)	Comparable	No correlation	
Zimbabwe	UN ACC-SCN (1992)	Comparable		
Zimbabwe	<i>Results presented here</i>	<i>Under-estimate</i>	<i>Correlated</i>	

Table 3.9: Summary of comparative studies of clinic-based versus survey-based assessments of nutritional prevalence

3.5 CONCLUSIONS:

The proportion of children participating in the growth monitoring programme has declined since the introduction of health fees under ESAP at the beginning of 1992. In 1988, estimated under-nutrition prevalence from a community-based survey of children below 5 years was broadly the same as that estimated by the NHIS. The comparison made here between the prevalence of under-nutrition amongst infants under 2 years from the DHS and NHIS suggests that the two are significantly different by about 1%. The difference between the prevalence of under-nutrition estimated by the NHIS and the actual prevalence may be even more pronounced when the 2-4 year age group is considered. Because of the difference in age groups considered between the 1988 study and the comparison presented here, however, no firm conclusions can be made about the change in levels of bias over time.

² The Botswanan system was able to distinguish three areas of high prevalence, but could not distinguish between 17 other districts. The El Salvador system was able to pick out two major sub-regions of high prevalence.

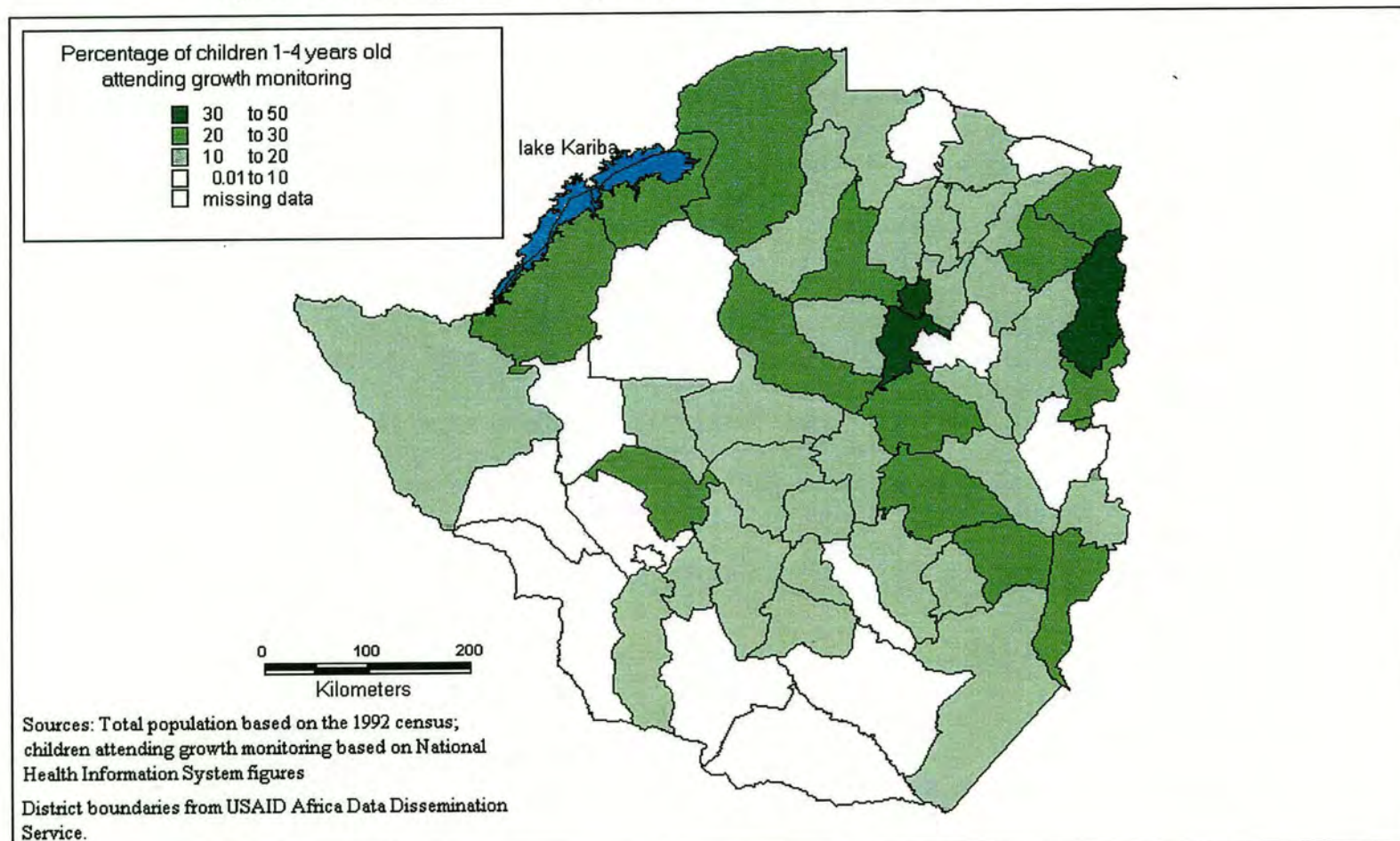
The proportion of children participating in growth monitoring varies considerably geographically. However, NHIS estimates of under-nutrition prevalence are significantly correlated with DHS estimates at provincial level. This suggests that the NHIS can be used for identifying provinces at risk, though prevalence estimates at district level requires further investigation. Furthermore, there is no evidence to suggest that there is any quarterly variation in attendance at growth monitoring, implying that NHIS data can be used to look at seasonal variations in underweight prevalence.

Several caveats should be made about the conclusions drawn here however:

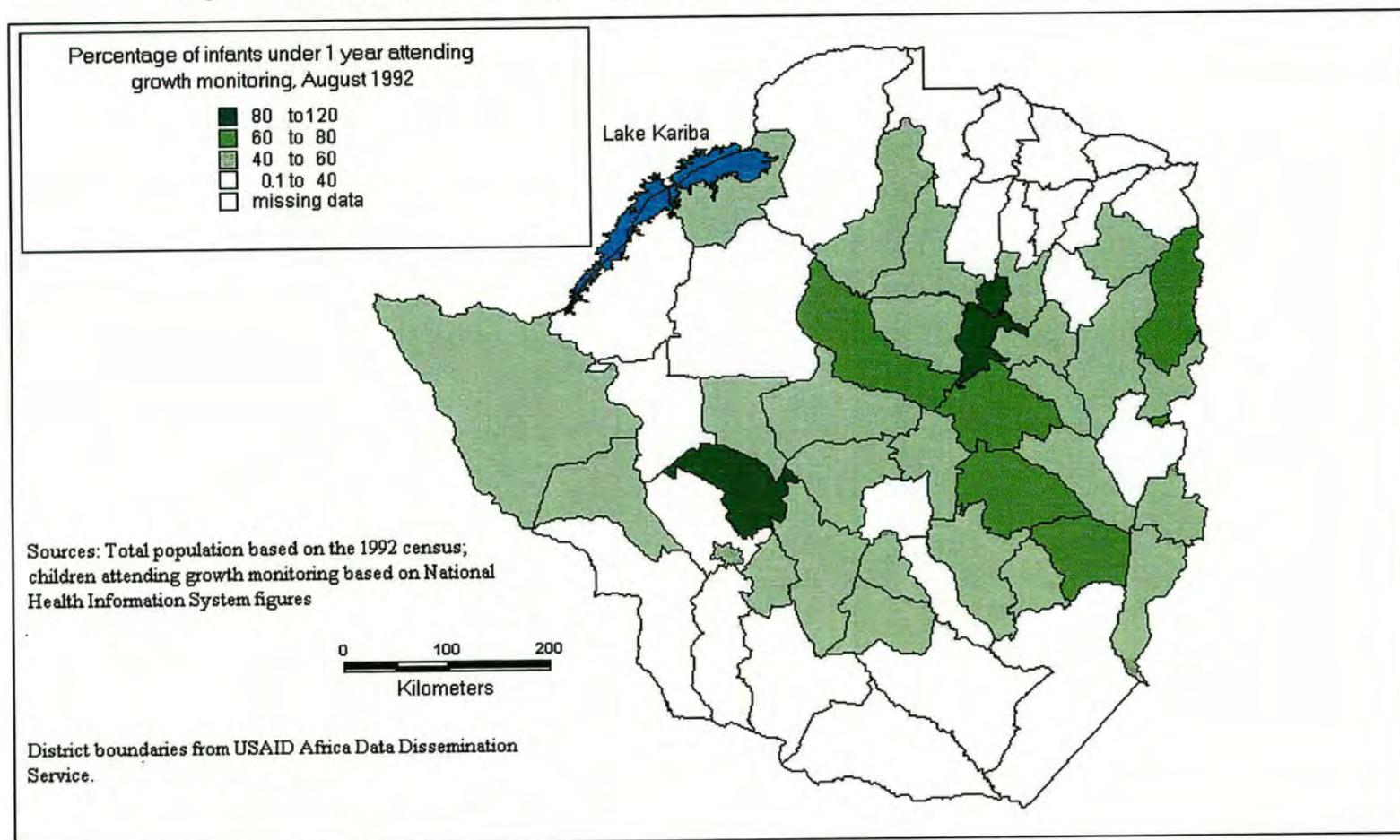
- Many of the tests here apply only to the younger participants in the growth monitoring scheme. In most cases, the evidence presented here concerns children under 2 years, although the NHIS scheme actually weighs children aged 2-4 years as well. It is quite likely that levels of bias are different among the 2-4 year age cohort. Children over 2 years old are *less likely* to attend growth monitoring, but more likely to be under-weight according to Tagwireyi and Greiner (1994). Therefore, bias in the under-nutrition rate amongst under-5s may be even higher than amongst under 2 year olds.
- There is also the possibility that the DHS survey itself is biased, since 4% of the children in the sample were not actually weighed.

Chapter 4 further explores seasonal aspects of underweight prevalence in the scheme, whilst Chapters 5 and 6 consider geographical and temporal patterns.

Map 3.1: Attendance at growth monitoring amongst children 1-4 years old, August 1992



Map3.2: Attendance at growth monitoring amongst infants under 1 year old, August 1992



4. Seasonal aspects of under-nutrition

4.1. Introduction:

This chapter assesses seasonal variation in levels of under-nutrition in Zimbabwean infants and young children. The chapter therefore explores Hypothesis E as described in the opening chapter of the thesis. Seasonality represents an area of interest for nutritionists, both for designing appropriate interventions and as an indication of the relative importance of the different causes of poor nutritional status (Sahn, 1989). Ferro-Luzzi *et al.* (1994), for example, compared seasonal weight loss in adults to an Index of Agro-Climatic Seasonality using a set of 26 different longitudinal studies around the world. They found that seasonal adult weight loss was greatest where agro-climatic seasonality was highest.

In Zimbabwe, Tagwireyi and Greiner (1994) have identified the three principal influences on children's nutritional status: household food security, health environment and services, and the level of care available within the household. Seasonal influences on each of these three pathways are examined here in two ways. Firstly, each pathway is considered in the light of field survey results from Buhera District. Secondly, patterns of under-nutrition within the country as a whole are assessed using growth monitoring data from the National Health Information System [NHIS].

4.2. Seasonal influences on child nutritional status:

This section briefly reviews seasonal aspects concerning the three influences on children's nutritional status described by Tagwireyi and Greiner (*ibid.*), using the survey results from Buhera District discussed in the previous chapter. As noted earlier, Buhera lies in a semi-arid part of Zimbabwe's communal lands, where smallholder farming predominates amongst a largely rural population. The survey used here took place between 1994 and 1995 and covered just under 1% of the district's population.

4.2.1. Household Food Security

The most obvious cause of variation in child nutritional status is through household food security. Tagwireyi and Greiner (*ibid.*, p. 48) note that 'in most years, households in at least some parts of the country are short of food between November and March'. In

Zimbabwe, even smallholder communal farmers purchase the majority of staple requirements through the marketplace. Corbett (1994), for example, found that in Chivi communal area, own production provided on average sufficient staples for only four months of the year, with the shortfall being made up through drought relief and purchases. The Buhera study indicates how the source of staples for consumption changed with season during 1995, as shown in Table 4.1. The proportion of surveyed households who acquired staples through the marketplace fell in June following harvest from 71.6% down to 59.9%. Because of the very poor harvests experienced in 1995, the number of households purchasing staples had risen to even higher levels by October. This confirms that rural households change the channels used to acquire food in the period leading up to harvest. A survey of expenditure patterns amongst the same households suggested that food purchases were the most important single item in the household budget.

Month	No of households surveyed	Percentage buying maize
February 1995	370	72%
June 1995	337	60%
October 1995	347	81%

Table 4.1: *Percentage of households in Buhera District acquiring maize through the market in 1995 at three different times of year.*

In terms of access to food for young children, this reliance on market purchases has two major implications. Firstly, in poor communal households, increased spending on staples can reduce the amount of money available for purchasing energy-rich infant foods such as beans, sugars, and fruits if these are not produced by the household itself. Secondly, the need for income for food purchases can reduce the time available for childcare, especially given that many communal household heads are women.

4.2.2. Household Care

Following earlier work by Almroth and Bidinger (1990) that highlighted the problems of water-based infant supplements, Tagwireyi and Greiner (1994) suggest that infants should be exclusively breast-fed up to the age of 4-6 months. Because of the small size of infants' stomachs, digestion of large meals is difficult and therefore frequent breast-feeding is necessary to ensure normal development. This also means that energy-rich foods are more appropriate as complements to breast-milk than maize gruel. However, at certain times of year, pressure on women's time may prevent such regular breast-feeding from taking place. Given that women do much of the agricultural work in rural areas, these times

are related to the cropping season as illustrated by Figure 4.1 below. It should be noted that this figure, which is adapted from FAO (1997), is a generalised depiction of the agricultural calendar for the whole country and that locally the timing of activities varies. For example, IIED/FSRU (1994) recorded agricultural labour patterns in the Chivi communal area and found peak agricultural activity occurring between October and March. Planting took place between October and November, followed by a limited amount of weeding and then harvesting between March and May. Such labour-intensive periods also provide an opportunity for earning income, and the Buhera study suggests that weeding in December/January may be the most important of these. Out of 355 households, there were 40 instances of people being hired to help with weeding compared to 10 for planting and only 4 for harvesting. As well as reducing the time available for childcare, high workloads for pregnant women can also directly affect the nutritional status of young children through the increased incidence of low birth-weight babies (Andren and Jacobson, 1986).

Wheat												
Maize												
Sorghum												
Test quarter	4	4	4	1	1	1	2	2	2	3	3	3
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep

Key:

	Harvesting
	Weeding
	Ground preparation, planing

Figure 4.1: Crop calendar for Zimbabwe (Source: adapted from FAO 1997. Note that winter wheat is only cultivated in irrigation schemes. The 'test quarter' row indicates how the year is divided into four quarters for the regression-based seasonality test described in 4.3.2)

4.2.3. Health status

Apart from changes in food consumption, nutritional status is also known to be closely related to health status. Disease can reduce the body's ability to digest food and suppress appetite, leading to possible weight loss and retarded growth in children (Tomkins

and Watson, 1989). In turn, poor nutritional status can reduce resistance to infection, leading to a 'malnutrition-infection complex'.

Disease	January-March	April-June	July-September	October-December
Diarrhoea	307,159 (1.4%)	283,791 (1.2%)	250,466 (1.1%)	283,980 (1.2%)
Acute Respiratory Infection	1,333,125 (5.9%)	1,306,415 (5.7%)	1,448,475 (6.3%)	1,317,632 (5.7%)
Malaria	223,564 (1.0%)	255,389 (1.1%)	148,054 (0.6%)	155,807 (0.7%)
Measles	12,119 (0.05%)	10,388 (0.05%)	18,747 (0.08%)	25,809 (0.11%)

Table 4.2: Total number of cases of four major childhood diseases by season reported in Zimbabwean children under 5 years, 1988-1992 (Source: National Health Information System, Government of Zimbabwe (1994e), Government of Zimbabwe (1989a) – figures represent cumulative number of reported cases over all five years. Figures in brackets are the percentage of population under 5 years reporting sick per month, based on a linear interpolation of population figures for 1987 and 1992.)

In Zimbabwe, peaks in cases of the major childhood diseases occur in different seasons, as illustrated by Table 4.2. This shows the number of reported disease cases by season. The Buhera survey suggested that there was no seasonal variation in the proportion of complaints reported at health centres and therefore that these figures are useful for distinguishing changes in prevalence by season. The proportion of complaints reported was 28% in November 1994, 30% in March 1995, and 29% in July 1995¹. The peak number of diarrhoea cases tends to be between January and March. This is in line with comments by Tagwireyi and Greiner (1994: p. 61) who note that:

'in the pre-harvest period people have difficulty obtaining access to food and suffer increased diarrhoeal disease as a result of the rainy season.'

The onset of the rains in October and November can wash faecal matter into unprotected water sources and contaminate supplies. Communities whose water supplies are protected, however, do not suffer such problems to the same extent. Unprotected water sources include streams, dams, and uncovered wells, whilst protected sources include boreholes, covered wells, and springs (Government of Zimbabwe, 1994e). Moy *et al.* (1991b), for example, found no seasonal increase in the incidence of diarrhoea during the rainy season in a longitudinal study of a community in Shamva District that relied on boreholes for its water supply. Other major diseases show different prevalence patterns by season. Table 4.2 indicates that acute respiratory infections increase in prevalence during the colder winter

¹ These figures are based on 302 sick individuals in November, 262 in March, and 298 in July. Jo Worrall of the IMFS project computed the statistics.

months, whilst malaria peaks in March and April immediately after the rains, as the mosquito population flourishes. Similarly, measles cases in Zimbabwe are concentrated during the October-December period. This broadly confirms the pattern described by Loewenson (1992: p. 78) in which:

‘in the 1985-86 survey, the increased incidence of reported ill health in agricultural labour households coincided with the May-July winter respiratory tract infection peak and the November-January wet season diarrhoea and malaria peak’.

Different stresses on nutritional status thus operate at different times of year. The pre-harvest period is characterised both by increased diarrhoea prevalence and poorer food access, whilst during harvest malaria prevalence increases and labour demands are high. Over the winter months, respiratory infections are common despite improved food access. Previous work also suggests that seasonal changes in nutritional status may vary geographically. The World Bank (1983) found that malnutrition was highest between October and November, based on monthly data on child hospitalisation due to malnutrition in Gwanda District. 60% fewer cases related to malnutrition were reported in April compared to November. Loewenson (1992: p. 78) reports seasonal peaks from March to May and again from October to December in the number of hospital admissions due to malnutrition reported at a district hospital in a large-scale commercial farming area. In contrast, Moy *et al.* (1991a) found that there was no seasonal trend in growth in farm workers’ children in Shamva District. They suggested that employment and earnings were constant throughout the year, so seasonal periods of food shortages did not occur.

4.3. Seasonal patterns in growth monitoring data

4.3.1. Data Quality Issues

Traditionally, the weight-for-height indicator, which reflects wasting or acute malnutrition, is used to examine seasonality (Ismail and Micklewright, 1997: p. 6). This is because children’s height changes gradually in response to nutritional problems, making height-for-age inappropriate for detecting intra-annual variations in nutritional status. Similarly, weight-for-age, as the indicator collected under the NHIS, is somewhat less likely to discriminate seasonal patterns, since it reflects both chronic and acute malnutrition.

As described in Chapter 1, although the NHIS provides monthly growth monitoring data with nation-wide coverage, several problems make interpretation of these data difficult. Random errors, such as miscalibration of weighing scales, incorrect age assessment, or transcription and data entry errors can occur (Ruel, 1995). Furthermore, the growth monitoring scheme includes only those who attend health centres for weighing, suggesting that the data may be biased. However, analysis of the number of participating children by month between 1988 and 1995 suggested that this remained fairly constant throughout the year. The total number of weighings averaged 1.11 million per year between January and March, 1.06 million between April and June, 1.14 million between July and September, and 1.11 million between October and December. This suggests little seasonal variation in participation in the weighing programme and this supports the conclusion drawn in Chapter 3 that there was no significant seasonal variation in growth monitoring attendance. This leaves the rather unlikely possibility that changes in the composition rather than total number of attendees may create a seasonal bias (for example, poorer, more underweight children attend growth monitoring in summer, whilst wealthier, less underweight children attend in winter). It seems highly unlikely, however, that a change in the type of attendee would not also be reflected in total attendance figures.

4.3.2. Method

Monthly growth monitoring data from the NHIS were obtained for the period January 1988 to March 1993 and for January 1994 to December 1995 for sixty different Zimbabwean districts. Several consistency checks were performed on the growth monitoring data prior to analysis. A check was made to ensure that the number of children weighed was always greater than the number recorded malnourished for all age groups. In addition, cases where identical figures had been entered onto the database for a district for two or more consecutive months were identified and omitted from the analysis. Given the scope for data entry, transcription, or aggregation errors in the system, extreme values were also flagged and excluded from subsequent analysis. Such values were identified by calculating the inter-quartile range² for each district and finding values which lay more than 3 inter-quartile ranges above or below the median. This flagging procedure was used both on the numbers of children who were weighed and on the percentage of children

² The inter-quartile range in this context refers to the difference between the 75th percentile and the 25th percentile of a variable's distribution.

underweight and is adapted from Haining (1990: p. 200). 1% of the total number of monthly data points were flagged using this procedure.

Linear regression was used to identify whether levels of under-nutrition increased significantly during any given season. Following the methodology outlined by Gujarati (1988), four dummy variables were created, representing the periods January-March, April-June, July-September, and October-December. Each dummy variable took a value of one during the period concerned and a value of zero at all other times of the year. Stepwise regression was then used to identify the combination of these dummy variables that best explained changes in the percentage of underweight infants and children in each district. The same method was also applied to pooled growth monitoring statistics nationally. Regression results were then verified by inspecting changes in under-nutrition prevalence over time graphically.

4.3.3. Results and Discussion:

Four main types of seasonal change in percentage under-nutrition were evident from this analysis. The spatial distribution of the four types is shown in Map 4.1, and their characteristics can be summarised as follows:

- **Type A** – *no significant seasonal change in percentage under-nutrition*. This was the most common type identified with 37 districts showing this pattern of seasonal change. None of the four dummy variables explained the observed pattern of under-nutrition, suggesting that there were no significant seasonal changes in weight-for-age malnutrition in children under 5 years in these districts. Table 4.3 shows the results of the regression analysis for one such district, Bindura (See Map 4.1 for locations of districts referred to in the text).
- **Type B** – *higher levels of under-nutrition in January-March*. 15 districts showed this type of seasonality and typical regression results are presented for Buhera District in Table 4.3. It can be seen from this table that only the dummy variable for January-March proved significant in explaining levels of under-nutrition in Buhera District. The fitted regression model suggests that weight-for-age malnutrition averaged 9.6% for April to December (as estimated by the constant term in Table 4.3), but increased significantly to 11.3% during January to March (as estimated by the constant term plus the dummy variable co-efficient for January-March in Table 4.3). However, the relatively poor ‘goodness of fit’ of this model suggests that there are other factors

influencing levels of under-nutrition. In many districts, one of the most important trends between 1988 and 1995 continued to be improved child nutritional status resulting from post-independence public spending in communal areas (see Chapter 5). Such trends are not reflected in the model presented here.

- **Type C – lower levels of under-nutrition during April-September.** 6 districts showed this type of seasonal pattern and typical regression results are shown in Table 4.3 for Matopos District. For this type of district, one of the two winter periods (April-June or July-September) showed significantly lower levels of weight-for-age malnutrition. In the case of Matopos district, the model in Table 4.3 suggests that the percentage of underweight children averaged 14.4% for most of the year, but fell to 12.82% between April and June. As with Type B, this seasonal model explains little of the variability in percentage under-nutrition, suggesting that other factors also affected nutritional status during this period.
- **Type D – higher levels of under-nutrition during October-December.** This pattern of seasonal change occurred in only two districts (Lupane and Kadoma). Table 4.3 shows the regression results for Lupane district, where the fitted model suggests an increase in mean percentage under-nutrition from 15.1% for most of the year to 16.7% in October-December. In the case of Kadoma, the regression analysis also indicated that levels of weight-for-age malnutrition were higher in January-March than in April-September (though under-nutrition was even more prevalent in October-December). Although this finding may reflect high levels of under-nutrition in the population as a whole in October-December in these two districts, the possibility of data collection errors should not be ruled out. Random errors (such as mis-typing of figures onto computer) could be the cause of the anomalous patterns of underweight prevalence in these two districts.

Type	District	Dummy Jan-Mar	Dummy Apr-Jun	Dummy Jul-Sep	Dummy Oct-Dec	Constant	Adjusted R^2
A	Bindura	n.i.	n.i.	n.i.	n.i.	--	--
B	Buhera	1.64 (*)	n.i.	n.i.	n.i.	9.64 (**)	0.046
C	Matopos	n.i.	-1.59 (*)	n.i.	n.i.	14.41 (**)	0.039
D	Lupane	n.i.	n.i.	n.i.	1.59 (*)	15.1 (**)	0.038
-	National	0.92 (**)	0.40 (*)	n.i.	n.i.	10.82 (**)	0.041

Table 4.3: Results of stepwise regression of seasonal dummy variables on percentage weight-for-age malnutrition for four sample districts (n.i. indicates that a variable was not included in the final model; * indicates significance at the 95% level; ** indicates significance at the 99% level; and 'national' refers to the model fitted to all the district statistics pooled together).

Given that 60 different districts were considered in this analysis, it was likely that at least some districts would have significant seasonal coefficients in the regression analysis by chance. However, a very large number of districts (23) showed significant seasonal coefficients and furthermore, results for 21 of these districts consistently suggested higher underweight prevalence pre-harvest. However, no clear geographical pattern of seasonality could be discerned from Map 4.1, except that slightly more districts in the south-east of the country displayed seasonality than in the north-west. Districts displaying higher underweight prevalence pre-harvest included urban districts (such as Mutare), more arid districts comprising Communal Areas (such as Buhera), and districts comprising mostly large-scale commercial farms in higher rainfall areas (such as Mazowe). The two anomalous districts that displayed an October-December peak in underweight prevalence – Lupane and Kadoma – were also different from one another. Kadoma is an urbanised district where mining is an important economic activity (Government of Zimbabwe, 1994e), whilst most of Lupane's population are subsistence farmers in the communal sector. Thus, there appears to be no grounds for suggesting that different types of community in Zimbabwe (such as urban wage earners or smallholder subsistence farmers) experienced different seasons of nutritional stress.

Nationally, the aggregate statistics followed a Type B pattern according to the schema above, as shown in Table 4.3. The co-efficients in this table suggest an underweight prevalence of 10.8% for the July-December period, rising significantly to 11.7% during January-March and falling again to 11.3% between April and June. This national-level analysis was consistent with the results of the more detailed assessment of the 60 districts.

These results are in keeping with those of an *ad hoc* report on growth monitoring data (Government of Zimbabwe, 1994f). This report suggested that the first or second quarters of the year were the times of greatest underweight prevalence for all but the 6-11 month age cohort, based on a visual inspection of graphs of underweight prevalence. These findings are confirmed by the regression results presented here.

4.4. Conclusions

The results presented here confirm that seasonality in under-nutrition rates occurs in Zimbabwe. In contrast to findings from some previous studies (World Bank, 1983; Loewenson, 1992), analysis of growth monitoring data suggests that the period before

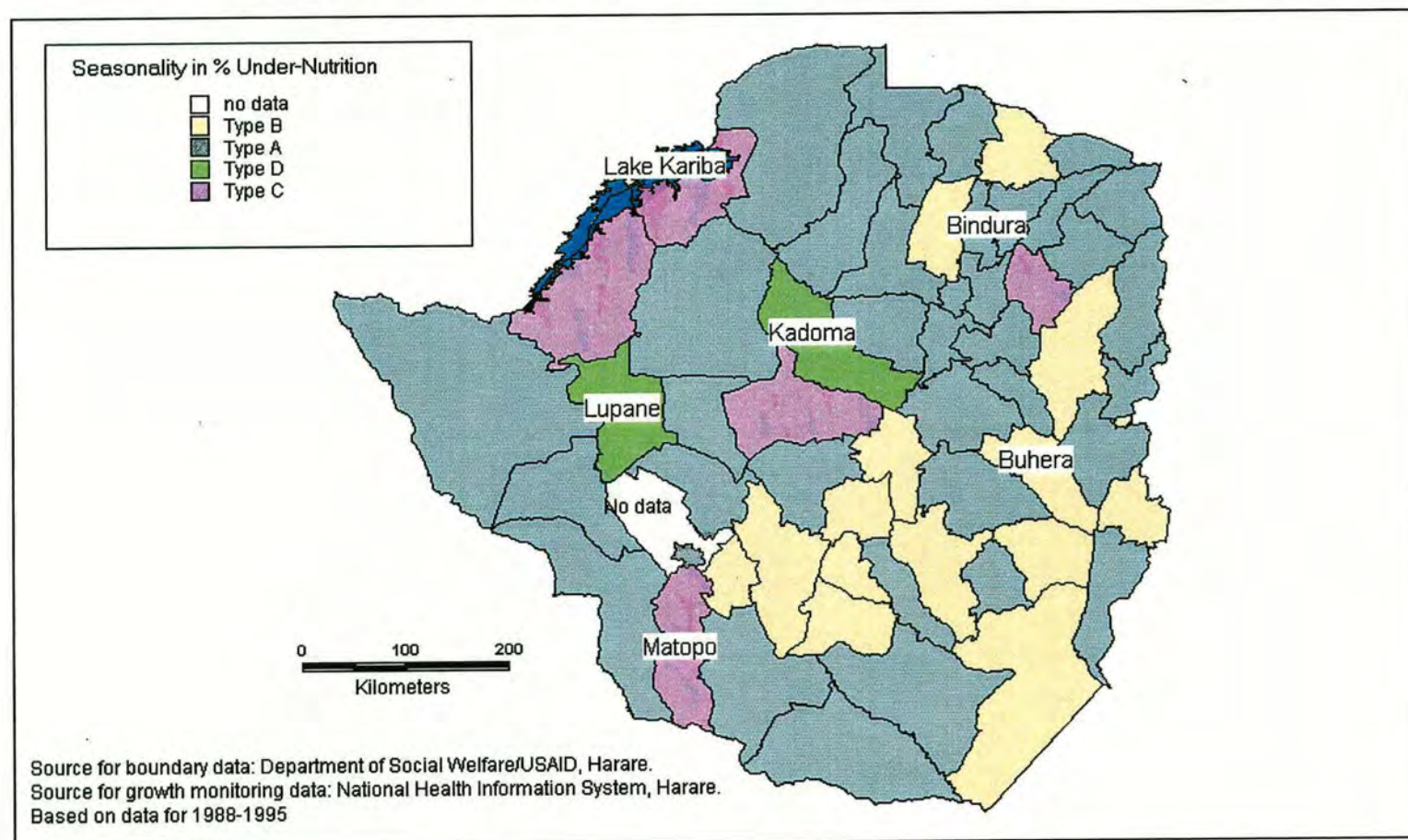
harvest is the time of greatest nutritional stress. This is borne out by the number of districts experiencing higher under-nutrition rates between January and March or lower under-nutrition rates during winter. This is likely to result from a combination of the higher incidence of diarrhoea, poorer food access as household budgets are dominated by market purchases of staples, and increased workloads for women in rural areas associated with planting and weeding. Stresses at other times of year (such as the rise in acute respiratory infections over winter and demands on women's time associated with harvest) appear to have less of an impact on child nutritional status. The consistency of regression results across many districts lends weight to this conclusion.

The growth monitoring data also confirm the observation that some communities feel these seasonal stresses more acutely than others do. In the majority of Zimbabwean districts, there was no evidence of seasonal change in nutritional status. Map 4.1 suggests that the districts that were found to have significant seasonal nutritional variation are concentrated in the south-eastern part of the country. However, there is no clear evidence here of any differences in seasonality between the communal and commercial sectors as suggested by Moy *et al.* (1991a), or between urban and rural districts.

This use of NHIS data also illustrates how secondary data collected by government can be used to corroborate the findings of more localised field studies. Such an approach has been recommended by Tagwireyi and Greiner (1994: p. 8), who have argued for:

‘better use ... of growth monitoring and other indicators in nutrition surveillance systems to guide resource allocation at each level of government’.

Map 4.1: Seasonal Patterns of Child Under-Nutrition in Zimbabwean Districts



5. LONG-TERM ASPECTS OF UNDER-NUTRITION

5.1 INTRODUCTION

This chapter uses nutritional monitoring data for Zimbabwe between 1988 and 1995 to test hypotheses D and F from Chapter 1, which concern trends and causes of under-nutrition. It is argued that three new forces – drought, the HIV/AIDS epidemic, and the Economic and Structural Adjustment Programme – should have increased levels of under-nutrition during the latter half of this period (see Section 1.4, Hypothesis D). The relationship of these new developments to the causal model of under-nutrition presented in Chapter 1 is shown in Figure 5.1. In addition, the chapter relates long-term socio-economic and physical characteristics of Zimbabwean districts to patterns of persistent weight-for-age malnutrition identified through the growth monitoring data. This analysis enables the relative contribution of health-related factors, such as sanitation and water source, and food access related factors, such as agricultural production system, to nutritional problems to be assessed (thereby examining Hypothesis F from Section 1.4). Causes of poor nutritional status identified in household surveys can thus also be investigated at district level using growth monitoring data.

Over the period under study, three threats to further improvements in child nutritional status have emerged. Firstly, the HIV/AIDS epidemic in Zimbabwe has clear implications for child nutrition. HIV prevalence is difficult to estimate, but figures based on sero-prevalence in pregnant women have suggested prevalence of 25% in this group (McCarty 1994; Tagwireyi & Greiner, 1994) and local prevalence as high as 30% (Gregson, 1995). Zanamwe *et al.* (1994) have suggested that the Zimbabwean HIV-positive population will increase from 800,000 as recorded at the end of 1992 to 3.75 million by the year 2000. Vertical transmission of HIV from mother to child is exposing an ever-growing number of young children to disease and consequent weight loss. As the number of orphan children grows, traditional means of caring for orphaned children are likely to come under increasing pressure. Zanamwe *et al.* (1994) have suggested that ‘much of the burden of orphan-caring may well fall on the elderly’ and this too may adversely affect their nutritional status.

The second threat occurred in 1991-92, when Zimbabwe suffered a drought which was ‘the worst in living memory’ (Scoones 1996: p 164), with mean annual rainfall only 24% of normal in parts of the communal lands. As a consequence, communal area grain production was negligible, and national strategic grain reserves exhausted. Employment

opportunities were also reduced – the Zimbabwean newspaper the Herald (1995: p.6), for example, described the effect of drought on employment in the sugar and tea industries:

‘At the height of the great drought of 1992, nearly 8,000 workers from Bottom Triangle and Hippo Valley¹ were either retrenched or placed on part-time. Massive retrenchments on tea plantations in the nearby Eastern Highlands, worsened the lot for people in the region, deemed one of Zimbabwe’s most productive.’

A massive relief operation began, with the first food aid arriving in the country in April 1992, and 4-5 million people receiving aid at the height of the drought (Scoones 1996: p. 175). The drought is likely to have affected not only access to food during 1992, but also to have reduced the asset base of much of Zimbabwe’s rural population. In Chivi district, only 34% of bulls and oxen survived the drought and the number of households who did not own any cattle rose from 55% to 68% (Scoones, 1996: pp 206-208). The effects of the drought were partly offset by strategies adopted by Zimbabwean farmers. For example, Kinsey (1998) found evidence that some households in Resettlement Areas with higher rainfall were taking care of cattle for some of those in drier areas. Similarly, Scoones (1990) found that certain farmers were able to reduce cattle mortality during drought by bringing their animals to graze on *dambos*² earlier in the season. Nonetheless, the effect of such erosion of assets is likely to have lasted well beyond the period of food shortage, with the loss of draught power being one result of such high cattle mortality. The nutritional impact of the drought should also be apparent in the growth monitoring data for some time after the event, given that the weight-for-age measure should reflect stunting (chronic malnutrition) as well as wasting.

The third threat to child nutritional status is the Economic and Structural Adjustment Programme (ESAP), adopted by the Government of Zimbabwe in 1991 under pressure from the World Bank and the International Monetary Fund (Moyo, 1995). The main thrust of ESAP has been to liberalise markets and to reduce public expenditure. The effects of the drive to reduce public expenditure are likely to have adversely affected the general well-being of the population of Zimbabwe (at least in the short-term). The policy was associated with public sector retrenchments (job losses) and cut-backs in expenditure on healthcare and public welfare. For example, between 1990 and 1994 expenditure per pupil on secondary education fell from Z\$630 to Z\$470 in real terms (Gibbon, 1996: p. 386). Although the number of actual civil service job losses may have been relatively small, public sector pay

¹ Two sugar plantations in south-east Zimbabwe. ‘Retrenchments’ are job losses.

² An area of wetter drainage, often artificially created by damming a water-course for the purposes of grazing cattle.

cuts were substantial. Gibbon (1996: p. 388) notes that an index of civil service real earning fell from 65 in 1990 to 34.6 by 1993. The impact of this reduction in earnings is likely to have been greater in the major urban centres, where many civil servants are located. At the same time, Marquette (1997) noted an increase in real prices of basic foods between 1990 and 1994. Bijlmakers et al (1996) detected a reduction in the number of food groups consumed by a panel of urban households in Chitungwiza over the same period. All of these factors would suggest that an increase in the prevalence of child weight-for-age malnutrition is likely, especially in the second half of the study period.

	HIV / AIDS Epidemic	Drought	ESAP
Food security	Reduction in household income generating capacity	Reduction in subsistence production and income from marketed produce through harvest failure. Reduced employment opportunities. <i>Possibly partly offset by drought relief.</i>	Retrenchments, especially in urban areas and fall in real wages. Urban price rises of meal, bread & other staples <i>Removal of grain marketing restrictions, improving rural access to grains through market</i>
Health environment	Secondary infections resulting from lowered immunity	Lowering of water table, increasing reliance on unprotected water sources may increase exposure to disease. State spending on drought reduced financial resources for healthcare.	Introduction of health fees Reduction in real healthcare expenditure since 1992
Care	Reduction in adult capacity to care for children Greater numbers of orphaned children without adult carers	Adults need to spend more time generating income from non-agricultural sources. <i>Possibly more time available for care at harvest, since many crops died before harvest.</i>	

Figure 5.1: Hypothesis D – consequences of recent developments in Zimbabwe and general factors affecting child nutritional status (the general factors in the rows are taken from Tagwireyi and Greiner, 1994. Positive consequences for child nutrition are shown in italics and negative consequences in a regular typeface.)

5.2 SELECTION OF INFRA-STRUCTURAL VARIABLES

Table 5.1 shows the socio-economic and physical variables that were postulated to affect aggregate nutritional status at district level. These variables were selected because they reflected one or more of the three principal influences on children's nutritional status proposed by Tagwireyi and Greiner (1994): household food security, health environment and services, and care for children. The variables selected are intended to represent persistent causes of poor nutritional status, which change slowly over time and are likely to have affected the under-5 population throughout the period under study.

Socio-economic variables were largely derived from the August 1992 census (Government of Zimbabwe, 1993d), which took place close to the mid-point of the period under study. Two variables (access to safe water and access to adequate sanitation) were selected for their impact on health status. Distance to water source was included separately because of its impact on the time spent fetching water by rural women, which reduces the time available for childcare, other household chores, and income generation (Burger and Esrey, 1995). Rukuni and Jayne (1995, pp. 9-10) suggest that Zimbabwean mothers with no formal education are two to three times more likely to have stunted or wasted children than those who have received secondary level education or higher. This may either be due to inadequate childcare or to poverty, but in either case the proportion of illiterate females aged 15 years or over was thus also included as an indicator.

Six other variables were considered to affect nutritional status through all three of the routes listed above, and also enabled the identification of major socio-economic groups within the population. The proportion of urban households in each district was selected because urbanisation profoundly alters livelihoods, changing diet and channels used to obtain food. This is supported by Madzingira (1995), who suggested that the distinction between rural and urban children under 5 years best explained the pattern of under-nutrition in the 1988 Demographic and Health Survey. The concentration of hospital and doctors in cities also means that healthcare availability is better than in rural areas (Chimhowu and Tevena, 1991).

5. Long-term aspects

Measure	proxy for:	Affects:	source
Proportion of households in traditional housing	extent of poor, rural households	Food, health & care	census
Proportion of households in mixed housing	extent of wealthy, rural households	Food, health & care	census
proportion of households in modern housing	extent of wealthy households	Food, health & care	census
percentage of urban population	extent of urban households	Food, health & care	census
proportion of households without safe water (i.e. using rivers/unprotected wells)	exposure to disease as a result of infra-structure	Primarily health	census
proportion of households with water source >1 km away	time available for childcare and income generation	Primarily care	census
proportion of households without any sanitation facility	exposure to disease as a result of infra-structure	Health	census
sex ratio in people over 15	proportion of female-headed households & reliance on remittance income	Primarily food and care	Census
mean annual precipitation	basic constraints on agricultural production	Food, health	CRES topographic & climatic database for Africa
proportion of area under commercial farming	nutritionally vulnerable commercial farm workers	Primarily food & health	Land Use Map
Density of road network	infra-structural development	Primarily food & health	Digital Chart of the World
proportion of women over 15 years illiterate	Childcare and weaning practices.	Primarily care	Census

Table 5.1: *Socio-Economic and Physical Variables Affecting Percentage of Underweight Children Under-5 for Zimbabwean Districts.*

In the rural sector, information on type of housing provides an indication both of wealth and market involvement. Participatory work on wealth ranking (Scoones, 1995) suggests that modern housing is restricted to the rural elite and the urban population and thus forms a suitable proxy measure of wealth. ‘Mixed’ housing (for instance, traditional dagga walls combined with tin roofs) suggests the presence of a wealthier rural group and poorer urban areas, whilst ‘traditional’ housing is associated with the rural poor. This hypothesis is

borne out by the Buhera field survey data described earlier in Chapter 2. Details of housing type were collected in October-November 1994, which were consistent with the definition used in the 1992 census. At the same time, information about thirty-four different types of agricultural and household asset was also included, using the questionnaire in Appendix 9. The results of this question were then used to produce an asset index, following a methodology suggested by Pastore (1994) that reflects the rarity of different assets. In this method, the proportion of households who do not own each type of asset is calculated. Similar types of asset (such as Scotch carts and water carts) are grouped before these proportions are calculated. Next, these proportions are summed for all of the assets that the household possesses to give the final index value. The index can thus be written as:

$$I_j = \sum_{i=0..n} (P_i * D_{ij})$$

(where I_j = asset index value for household j ; P_i = proportion of households not owning asset i ; and D_{ij} = dummy variable, taking a value of one where household j owns asset i , otherwise taking a value of zero)

This asset index thus reflects household wealth. To assess the relationship between wealth and housing type, as defined in the 1992 census, an analysis of variance was performed on the Buhera survey data. Table 5.2 gives descriptive statistics for the asset index assessment, broken down by housing type. Tukey's honestly significant difference test (SPSS, 1993) was performed on these data to identify whether there were significant differences in the mean values of the asset index for any of the three housing types. This statistic is significant when:

$$MEAN(I) - MEAN(J) \geq 0.0754 * RANGE * \sqrt{(1/N(I) + 1/N(J))}$$

(where I and J are the two groups under consideration and $N(I)$, $N(J)$ are the number of households in each group)

It was found that households with mixed or modern housing had significantly higher asset index values compared to those who lived in traditional housing (though no significant differences existed between modern and mixed housing). This suggests that housing type is a suitable proxy for household wealth, at least in Buhera district.

Housing type	Mean asset index	Standard Deviation of asset index	No of households
Modern housing	0.22	0.152	35
Mixed housing	0.21	0.138	89
Traditional housing	0.11	0.085	263
For Entire Population	0.15	0.117	387

Table 5.2: Descriptive statistics for asset index by housing type for sample survey households in Buhera district, October 1994.

Another important subset of Zimbabwe's rural population are the workers in the Large Scale Commercial Farming (LSCF) sector, formerly known as the European Areas under colonial rule and UDI. The extent of this group was represented by the proportion of land under the LSCF sector, which was calculated by overlaying a district boundary map on land use boundaries within a geographical information system (GIS). Food access for this group tends to be through market purchases, rather than through subsistence production. Amanor-Wilks (1995) has argued that the commercial farming workforce is among the most nutritionally vulnerable in Zimbabwe today, having benefited much less from post-independence improvements in education and healthcare than the Communal Areas. In addition, the widespread employment of labourers on a seasonal contract basis makes commercial farm workers' wages and food purchasing ability dependent on an unreliable source of income (Rukuni and Jayne, 1995: p. 11). The Communal Areas consist of lower potential land set aside for the indigenous population during the colonial period and tend to act as reserves of labour both for the cities and the LSCF. As a result, many communal households are dependent on remittance income from absentee adult males, whilst women are responsible for agricultural work and childcare. Following Zanamwe's (1991) study of district age-sex structure, adult sex ratio was used as an indicator of these areas of male out-migration.

Finally, two further variables were included which were related to the physical characteristics of each district. Mean annual rainfall for each district was used as a measure of one of the basic constraints on agricultural production. This was calculated using a GIS by overlaying district boundaries on a mean annual rainfall image for the period 1920 to 1980 derived by Hutchinson (1997). Rainfall data are discussed in greater detail in section 2.1.5 and Chapter 6. As a measure of infra-structural development within each district, the density of the road network was similarly calculated by overlaying district boundaries on a digital road map taken from the Digital Chart of the World (ESRI, 1991).

5.3 PRE-PROCESSING OF GROWTH MONITORING DATA

Several logical checks were performed on the growth monitoring data to identify inconsistencies in the data prior to analysis. The logical checks described in 4.3.2 were performed on the data to check for consistency and identify outlying values. Figure 5.2 illustrates outlying values flagged using this method for Gweru District. Finally, the number of children weighed and the percentage of underweight children were examined as time series graphs to identify changes in growth monitoring administration procedures.

As a result of changes in administrative procedures, several districts' data were re-organised for the purposes of the analysis. Information for Zvimba district, which was created when Makonde District was divided in two in 1992, was aggregated with that for Makonde District (see Map 5.1 for locations of places referred to in the text). In the 1994-95 period, it was difficult to distinguish between Mutare Rural District and Mutare Urban District, so information for 1988-93 only was used to assess nutritional status trends in these two districts. Chipinge and Chimanimani Districts also underwent changes in reporting procedures in December 1991, so these two districts were also aggregated together. Information from the growth monitoring scheme which operated during 1991-92 in Tongogara Refugee Camp in Chipinge, which housed Mozambicans displaced by the civil war, was excluded from the analysis. Finally, Umguza district, for which growth monitoring information was only available for 1994-95, was excluded from the analysis described below.

5.4 METHODOLOGY

5.4.1 *Curve-fitting*

To characterise the nutritional situation for each district, the mean and trend in percentage of underweight children were estimated as a function of time using linear regression:

$$Y_t = \beta_1 t + \beta_0 + \varepsilon_t \quad (1)$$

(where Y_t = percentage of children underweight at time t ; t = time in months; and ε_t is the residual error term)

Time was measured in months and standardised so that the mid-point of the time series (the end of 1991) was zero. This meant that the intercept term of the regression equation, β_0 , was an estimate of the mean malnutrition rate for the period. Given that the number of months of available data varied between districts, this provided a more comparable measure of average nutritional conditions than the arithmetic mean of the monthly rates. The fitting of this equation is illustrated for Gweru District in Figure 5.2.

5.4.2 *Principal Components Analysis*

Because of the large number of socio-economic and physical variables in Table 5.1, a data reduction technique was used prior to investigating their relationship with nutritional status. The variables were submitted to a principal components analysis³, which reduced them to a smaller set of abstract, orthogonal factors whilst retaining most of the variation in the original data set. The small number and lack of correlation between the resultant factors makes them suitable for subsequent regression analysis, although their abstract nature makes their interpretation more difficult than methods which use the original variables directly.

5.4.3 *Regression Analysis*

The relationship between the physical and socio-economic district characteristics and the estimated mean percentage underweight was investigated using linear regression. The factors from the principal components analysis representing physical and socio-economic conditions were regressed against the intercept term (β_0) from equation (1), which was an estimate of the mean percentage of underweight children within each district. This tested the strength of the relationship between mean percentage underweight and the districts' physical and socio-economic characteristics.

5.5 RESULTS

By way of illustration, Figure 5.2 shows the change in the percentage of underweight over time for Gweru district. The fitted regression line based on equation (1) is also shown,

together with extreme values identified during initial data exploration and excluded from the analysis.

Map 5.1 shows the intercept term from the linear regression of time against percentage weight-for-age malnutrition. This term corresponds to the mean percentage of underweight children during the period 1988-95 and several geographical patterns can be discerned. Urban areas (Bulawayo, Mutare City, Harare, and Chitungwiza) show lower rates of weight-for-age malnutrition than rural areas. The proportion of underweight children in these areas is close to the 3% figure which would be expected in the WHO standard population. The situation in Binga District on the shores of Lake Kariba is considerably worse than any other part of Zimbabwe. The more arid parts of the country in Matabeleland, the Zambezi valley, and northern Mashonaland show higher weight-for-age malnutrition than the highveldt areas in the centre of the country.

Map 5.2 shows the slope term from the linear regression of time against percentage of children underweight. Figure 5.3 shows the slope co-efficient for weight-for-age undernutrition (β_1) plotted against the intercept term (β_0) from equation (1). In 49 districts out of a total of 57, the trend in underweight over the period 1988-95 was downwards, whilst in 6 districts there appeared to be no significant trend. Weight-for-age malnutrition had increased significantly in only 2 districts (Gweru and Mutare), both of which showed very low percentages of under-weight children at the start of the time series in any case. The trend in the proportion of underweight children is lower in districts where the mean level of child malnutrition is low. Again, the percentage of underweight in Binga District lies well above the national average, though the situation there has been improving by 1.8% per year over the study period. In addition, however, two districts of rural Matabeleland (Tsholotsho, and Nkayi Districts) show high levels of weight-for-age malnutrition, which have not been reduced significantly over the study period.

³ Factors with eigenvectors greater than 1 were retained and no rotation was performed on the extracted factors.

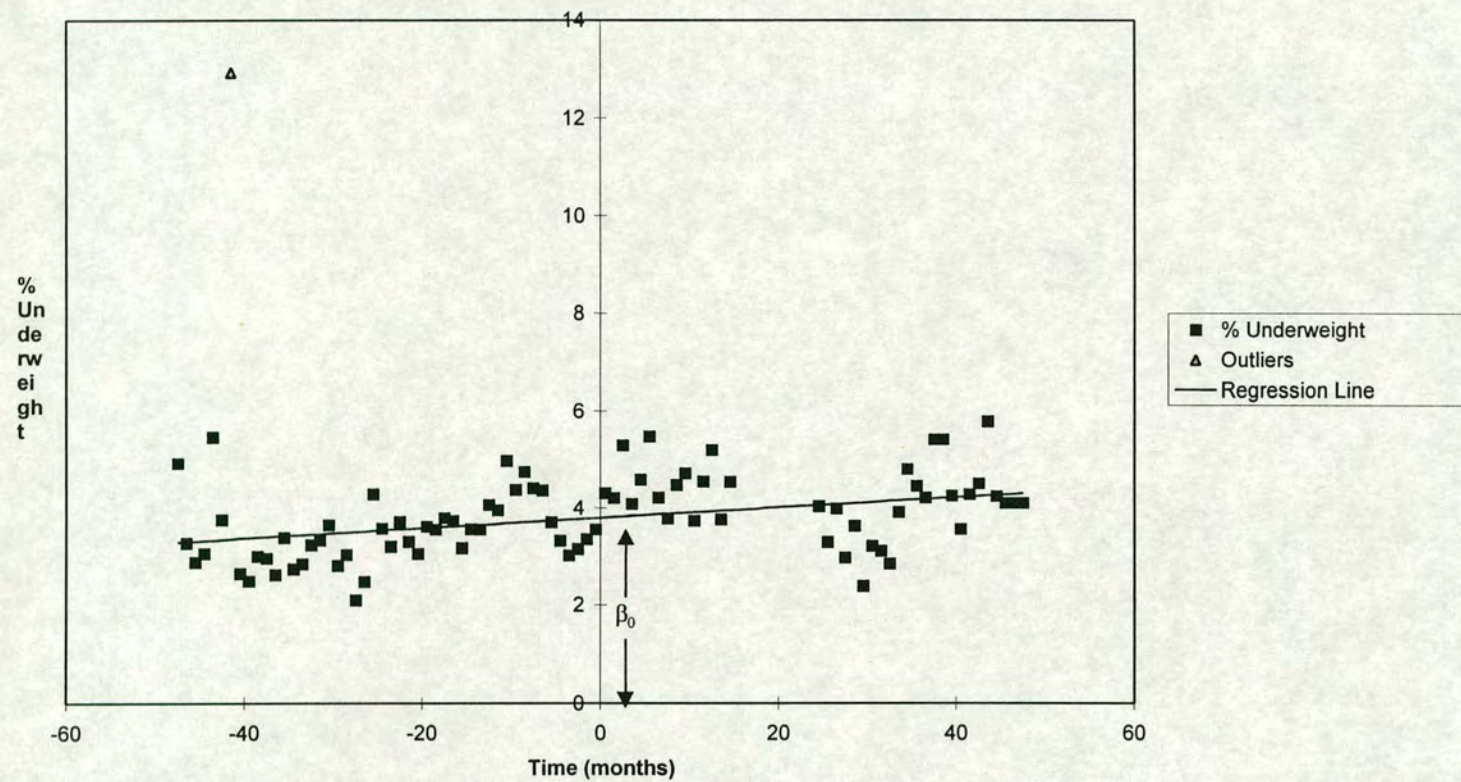


Figure 5.2: Graph of change in percentage of underweight children for Gweru District, 1988 – 1995 (the regression line based on equation [1] is also shown)

The principal components analysis reduced the original data set to four orthogonal factors, which accounted for 80.9% of the variation in the original variables. Table 5.3 shows the proportion of the total variation in the original variables accounted for by each of the four factors identified.

Table 5.4 shows the factor loadings from the principal components analysis, which reflect the correlation between the original variables and the extracted factors. These extracted factors can be broadly characterised as follows:

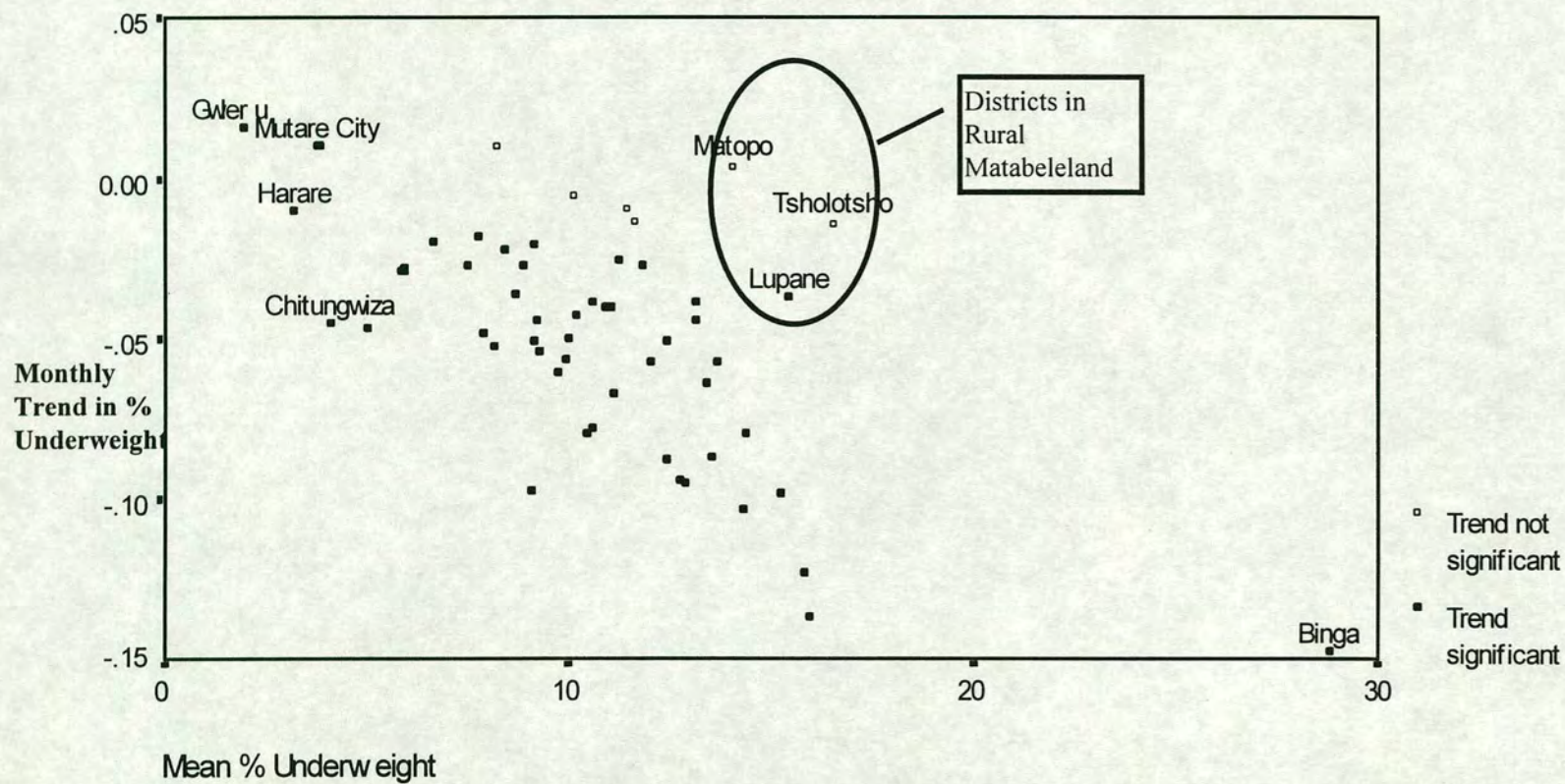
- The first factor was strongly related to the proportion of households in traditional housing, the proportion of households with unsafe sanitation, the proportion of households more than 1 km from a water source, the proportion of households with unsafe water sources and inversely correlated with the proportion of urban households and households in modern housing. This factor appeared to represent *rural living conditions*.
- The second factor was primarily related to mixed housing and to a lesser extent with mean annual rainfall. This factor appeared to represent the *extent of a wealthier rural group*, able to afford more expensive housing materials.
- The third factor was related to *road density*, though somewhat weakly.
- The fourth factor was positively associated with male: female ratio and negatively with the proportion of land area under commercial farming. This appeared to represent those *communal areas* that are a source of labour for the LSCF and urban areas.

The communalities in Table 5.4 indicate the proportion of the original variance in each variable accounted for by all the four factors combined. Thus, sex ratio, road density, and mean annual rainfall were the three variables most poorly represented by the final set of factors.

Factor	% of total variance explained	Cumulative % of total variance explained
1	44.1	44.1
2	16.4	60.5
3	10.5	71.0
4	9.9	80.9

Table 5.3: *Percentage of Variance Explained by Factors from Principal Components Analysis.*

Figure 5.3: Mean percentage under-nutrition and trend in percentage under-nutrition for Zimbabwean districts, 1988-1995



Variable	Communality	Factor 1	Factor 2	Factor 3	Factor 4
% of LSCF land	.81	-.22	.45	.38	-.65
% of illiterate women over 15 years	.83	.70	-.24	-.45	-.27
Mean annual rainfall	.73	-.23	.60	-.54	.18
Male: female ratio	.48	-.19	.04	.10	.65
% of households in 'mixed' housing	.88	.19	.90	.21	.06
% of households in 'non-traditional' housing	.97	-.95	-.26	-.09	.01
Road density	.64	-.36	-.10	.66	.24
% of urban households	.93	-.88	-.33	-.17	.13
% of households in 'traditional' housing	.94	.95	-.17	-.01	-.04
% of households using unsafe sanitation	.87	.89	-.16	.12	.20
% of households with water sources >1km away	.83	.77	-.40	.28	.02
% of households using unprotected water sources	.81	.73	.39	-.06	.35

Table 5.4: Factor loadings for socio-economic and infra-structural variables from principal components analysis (Figures in bold indicate the strongest factor loadings for each variable).

Table 5.5 shows the results of the linear regression of the four factors against the intercept term from equation (1), β_0 , representing mean malnutrition during 1988-1995. Factors 1 and 2 were found to be significantly related to the intercept term for the 57 districts. The R^2 value for the fitted equation was 0.63 and the F-Statistic for the regression was significant at the 99.9% level. The relationship between mean under-nutrition for 1988-1995 and the first factor is also shown in Figure 5.4.

Coefficient	Significance of T
Factor 1	***
Factor 2	**
Factor 3	n.s.
Factor 4	n.s.
(Constant)	***

Table 5.5: Results of Linear Regression of Factors Extracted from the Principal Components Analysis on Mean Malnutrition Rate for 57 Districts (*** = significant at the 99.9% level; ** = significant at the 99% level; n.s. = not significant)

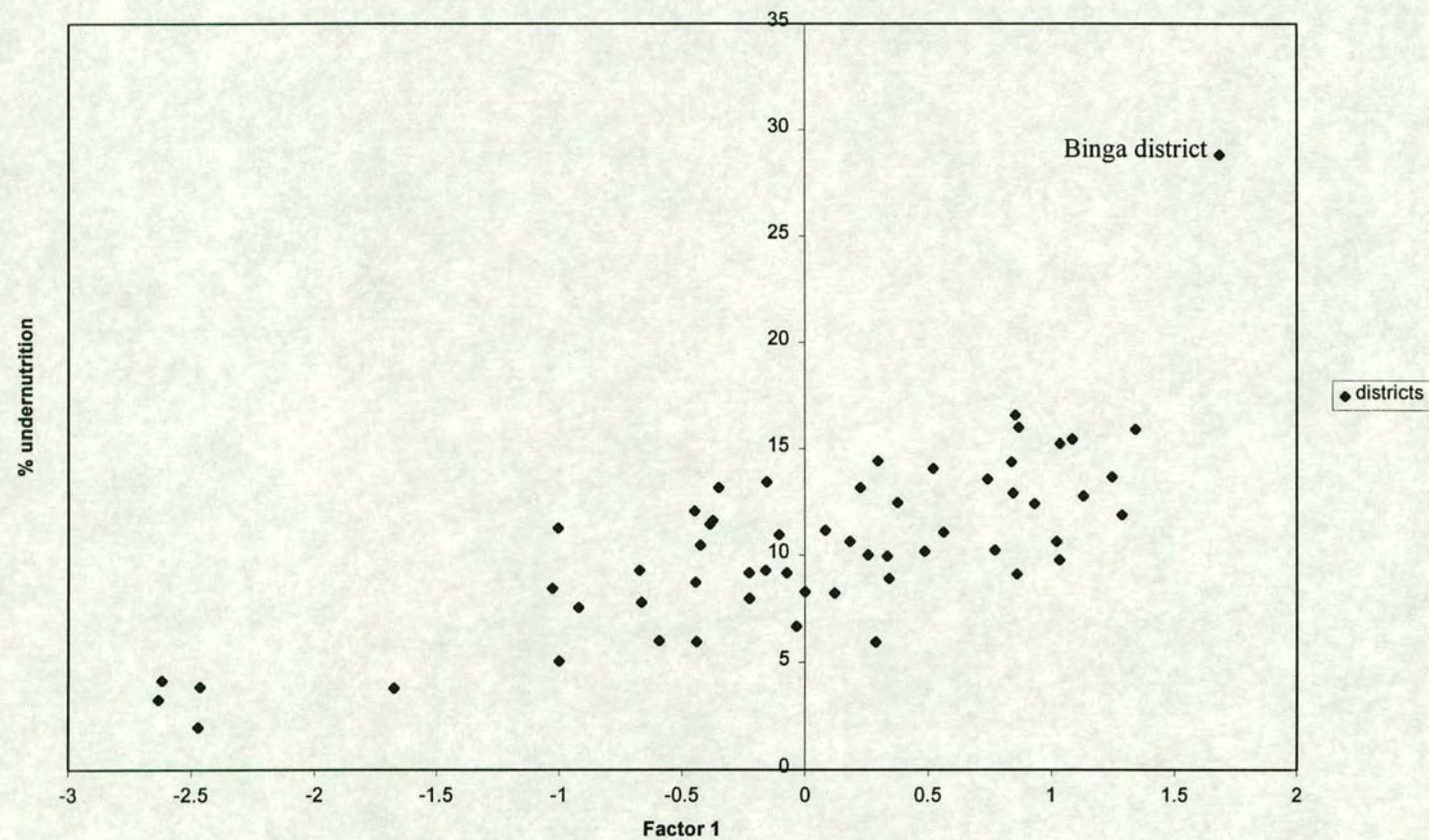


Figure 5.4: Scatterplot of mean under-nutrition among children under 5 years (1988-1995) and Factor 1 from Principal Components Analysis (Factor 1 represents rural poverty)

5.6 DISCUSSION

5.6.1 *Long-Term Trends*

The overall reduction in weight-for-age malnutrition reflects the findings of Bijlmakers *et al.* (1996) for the mid-part of this time series. They noted that ‘no negative trend has been observed with respect to child nutritional status. UNICEF (1994) reports that several sources indicate that overall malnutrition levels remained remarkably consistent during the period 1989-1992’ (ibid, p. 14).

It is also confirmed by an analysis of NHIS data for 1988-1993 (Government of Zimbabwe, 1994f). This study, based on visual inspection of time series graphs of percentage underweight, found that underweight prevalence had generally declined amongst children under 5 years, though a slight increase occurred after the drought in 1993. Overall, however, this trend is somewhat surprising given the combined effects of the HIV/AIDS epidemic, structural adjustment, and drought discussed at the start of this chapter.

One possible explanation as to why these three factors do not appear to have exacerbated weight-for-age malnutrition during the study period is in the Zimbabwean government’s commitment to improving rural living conditions. The post-independence period witnessed increased expenditure in rural development and health (Government of Zimbabwe, 1990). The benefits of several of the measures adopted - which included the establishment of a primary healthcare service, free healthcare for low income groups, investment in sanitation and water facilities, and the introduction of a child supplementary feeding programme - may still be reducing the prevalence of underweight in under-5s, even though most were introduced prior to the period under study. In addition, the government also maintained food security in rural areas during periods of drought through its drought relief programme. Marquette (1997: p. 1144) has argued that the scale of this programme may have lowered under-nutrition prevalence in some areas:

“The Sentinel Site Surveys indicated that three quarters of households in rural areas applied for drought relief in 1993 and that malnutrition in the country did not worsen (and in some areas of the country it actually improved after 1991).”

An alternative explanation for the changes in under-nutrition rates might lie in market liberalisation reforms introduced under ESAP. Whilst the effect of public expenditure reduction is likely to have adversely affected nutritional status, the effect of market reforms may be more complex. Although some have argued that the removal of

price controls designed to protect lower income groups can only be detrimental to the poor (Kadenge, 1992), the effect of market liberalisation on nutritional status may not be quite so straightforward. It is known that the tightly controlled maize marketing policies of the 1980s channelled grain surpluses into cities, inhibited rural grain processing capacity, and encouraged distribution and consumption of highly refined, less nutritious, commercial maize meal (Jayne and Chisvo, 1991). Restrictions on grain trading between rural areas also existed under this system, making it more difficult for rural communities to access surpluses in neighbouring areas. Following the lifting of these restrictions under ESAP, access to more nutritious, coarse-run meal from local mills may have reduced under-weight prevalence in rural areas, albeit at the expense of urban consumers. Recent work confirms that one consequence of liberalisation has been greater movement of grain from surplus to deficit rural areas (Vaze *et al.*, 1996). This explanation is consistent with the improvements in nutrition in rural areas and the lack of improvement in cities evident in the growth monitoring scheme. However, it might be argued that increased access to more nutritious, coarse-run grain would benefit adults more than the young children considered here.

The reduction in underweight prevalence may also reflect the ability of apparently vulnerable households to cope during times of hardship. During the 1991/92 drought, for example, communal households used a wide range of coping strategies to sustain themselves - including working off-farm, pottery-making, selling vegetables, beer, or livestock, and gold-panning (Scoones, 1996). There is, of course, no guarantee that such strategies will continue to be successful in the future under conditions of prolonged stress.

A third possibility is that the growth monitoring data do not adequately represent the trend in weight-for-age in the Zimbabwean under-5 population as a whole. This would imply that the degree of bias in the subset of children who participate in the programme has changed over time. The obvious cause of such a trend would be ESAP itself. This has led both to a reduction in healthcare funding and the introduction of user health fees as part of a cost-recovery programme. Both these policies may have adversely affected growth monitoring attendance and, as described in Chapter 3, the proportion of children attending growth monitoring nationally has in fact declined since 1992. This scenario therefore represents quite a plausible explanation of the apparent decline in underweight prevalence.

5.6.2 *Areas of persistent under-nutrition*

In terms of the geographical distribution of malnutrition, three interpretations may be placed on the patterns shown here. One interpretation would be that the variability is due to the environment, as represented in the PCA factors. The high prevalence of weight-for-age malnutrition in Binga District, for example, may be explained by the living conditions within the district. The socio-economy of this district has been examined in detail by Muir (1993) who found that opportunities for income generation or agriculture were limited and that the Tonga people in the district were heavily reliant on food aid for a living. The principal components analysis showed that the proportion of households lacking adequate sanitation and water supplies, living in traditional housing, and the proportion of illiterate women were related to urbanisation. The significant relationship identified by the linear regression between the first factor, which appears to represent the proportion of rural population, and the mean percentage of underweight children is therefore unsurprising. This is consistent with the 1988 DHS survey which found 'substantially more stunting in the rural areas, but not much wasting in either urban or rural areas' (UN ACC-SCN, 1992: p. 10). The second extracted factor, which was strongly related to the proportion of households living in 'mixed' housing was inversely related to mean percentage weight-for-age malnutrition. This is consistent with the suggestion made earlier that such 'mixed' housing was indicative of the presence of a wealthier rural group who are less vulnerable to the causes of malnutrition than the poor. Other studies at national level have produced similar findings: Frongillo *et al.* (1997) found correlation between socio-economic and demographic factors and levels of child under-nutrition in a study of national nutritional data from several continents.

However, an alternative explanation for the geographical pattern of underweight prevalence is based on genetics, rather than the Tagwireyi and Greiner model of nutritional status presented in chapter 1. The standard reference population used to define the cut-off point for underweight children on the health card consists of healthy Americans. Tanner (1994: p. 2), however, has suggested that genetic differences even amongst siblings 'exert in general, much more force than environmental ones'. By the same argument, the geographical differences in prevalence may be related more to genetic differences between populations than the environmental influences represented by the PCA factors. Ethnically, for example, the Tonga people in Binga, the district with the highest levels of under-nutrition here, are different from the inhabitants of the rest of the country. Similarly, the Matabele in

western Zimbabwe are ethnically distinct from the majority Shona group. Whilst genetic differences between these groups cannot explain rural-urban differences in prevalence, they may contribute to inter-rural variability in percentage under-nutrition.

The third explanation for the geographical patterns presented here is that the growth monitoring data may misrepresent the true district-level prevalence of under nutrition – in other words, the patterns seen here are simply an artefact of the data collection method. In chapter 3, it was shown that NHIS estimates of percentage underweight were well correlated with those in a community-based survey at the provincial level. This suggests that the data are reasonably reliable for ranking provinces by underweight prevalence, but there is no guarantee that this is also true for the district-level estimates presented here.

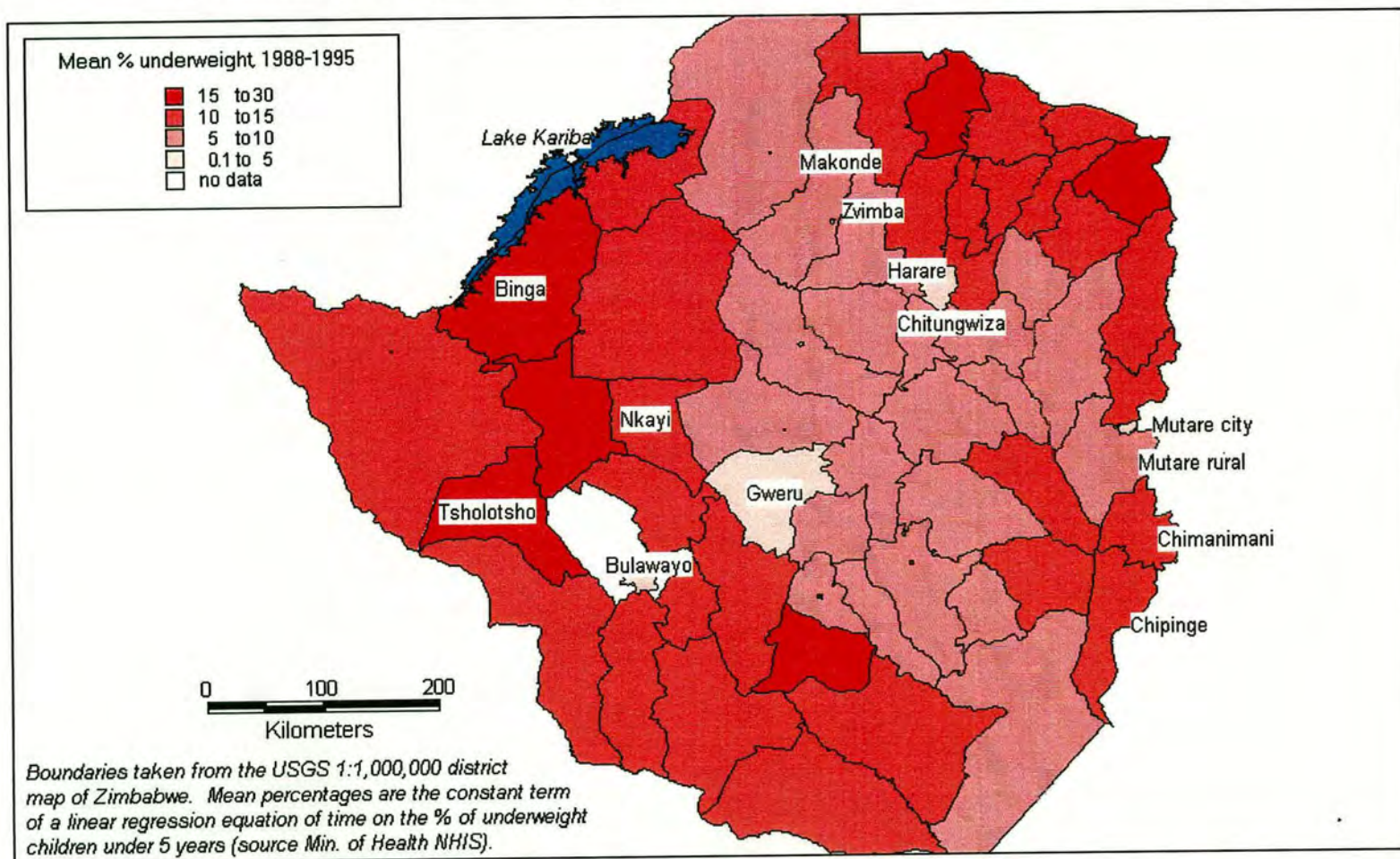
The apparent persistence of a high proportion of underweight children in parts of rural Matabeleland is consistent with findings presented by Rukuni and Jayne (1995: p. 7), based on a province-level analysis of data on stunting. It also accords with comments made by Bijlmakers *et al.* (1996: p. 14) that ‘Malnutrition...is more prevalent in the drought-prone provinces of Matabeleland North and South and Masvingo’. Tagwireyi and Greiner (1994: p. 19) similarly confirm that ‘there is a general trend towards improvement, except possibly in the worst-off areas, the Matabeleland provinces and Mashonaland Central’. Rukuni and Jayne (1995) attributed the lack of an improvement in stunting in Matabeleland to the particular severe succession of droughts experienced in the area in the late 1980s. However, this does not explain the persistence of a high proportion of underweight children throughout the 1990s.

5.7 CONCLUSIONS

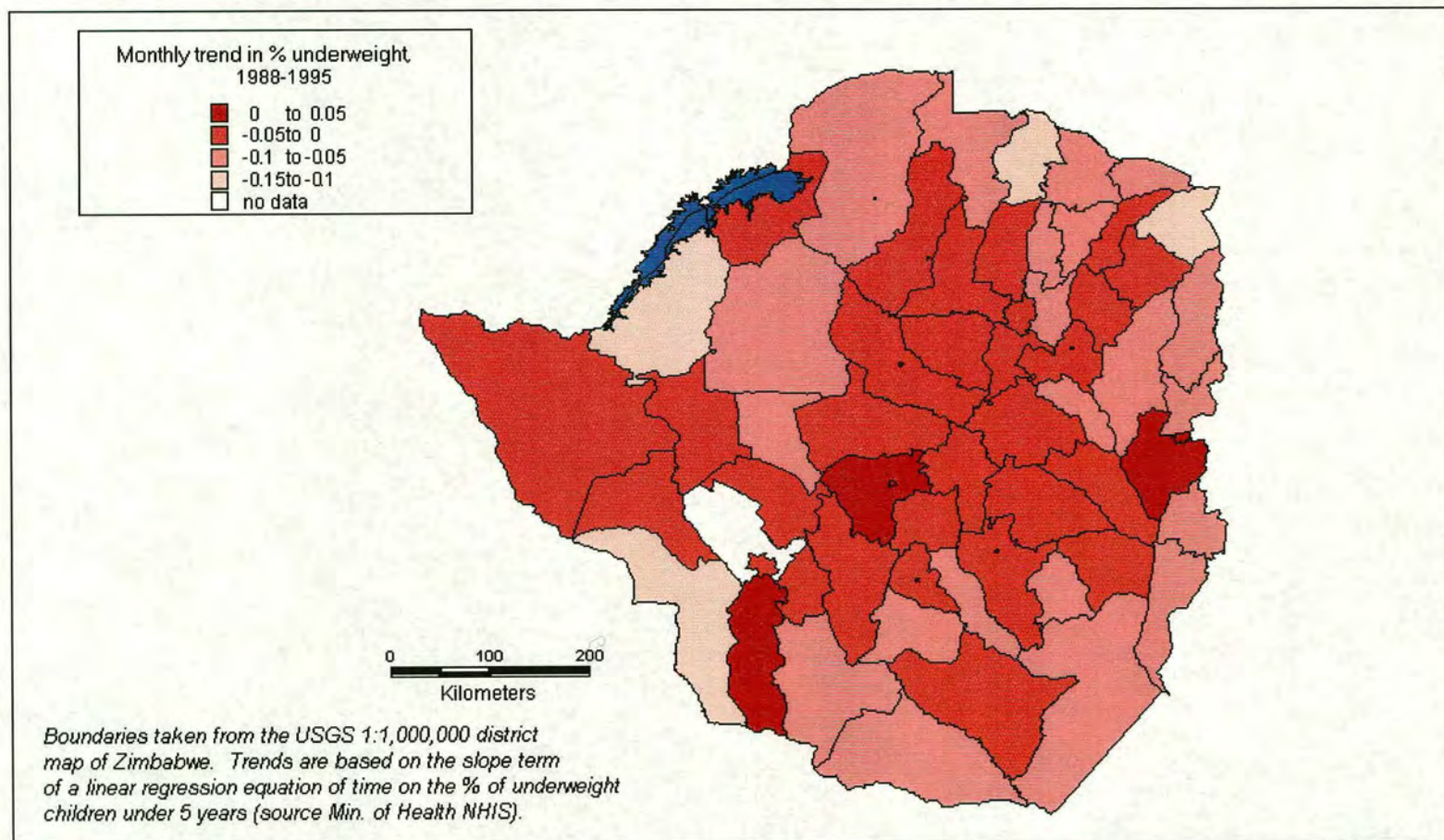
Overall, therefore, the longer term patterns of underweight prevalence are consistent with expectations in some respects but inconsistent with them in others. Geographically, the presence of greater levels of under-nutrition in rural areas is unsurprising given the poorer living conditions outside the major cities. These living conditions not only reflect levels of wealth, but also the health environment (water source and sanitation), suggesting that these health-related factors are also correlated with long-term under-nutrition. However, the continued reduction in underweight prevalence is contrary to expectations, given the problems of drought, HIV/AIDS, and structural adjustment. The growth monitoring data

indicate that under-nutrition has increased in some areas, notably rural Matabeleland and Zimbabwe's major cities. It is, however, conceivable that these apparent trends could result from changes in healthcare provision and funding rather than 'real' changes in the 0-4 year population as a whole.

Map 5.1: mean percentage of underweight children under 5 years by district, 1988-1995



Map 5.2: trend in percentage of underweight children under 5 years by district, 1988-1995



6. Annual and monthly aspects of underweight prevalence

6.1 *Introduction:*

This chapter explores short-term variability in under-nutrition levels. The previous chapter showed that the long-term average percentage of underweight children could be related to both the health environment and socio-economic factors. This chapter assesses the relationship between short-term variability in under-nutrition levels and health and food-security related indicators. It was suggested in the introduction that health-related factors are at least as important as those related to food access (Hypothesis F) and this idea is considered here. The analysis is divided into two sections. In the first section, annual changes in under-nutrition are considered, whilst in the second section, monthly changes are considered. This approach was adopted because many indicators are only available on an annual basis.

Finally, the chapter develops a method for forecasting changes in under-nutrition. This explores the idea that forecasting is possible from secondary data alone, as proposed in Hypothesis C in the introduction.

6.2 *Data*

6.2.1 Preparation of nutritional status data

The first stage in assessing annual levels of malnutrition is the definition of a suitable dividing point between successive years. The approach adopted here follows that of NEWS (Government of Zimbabwe, 1994b), who used an agricultural year beginning in April and ending in March to analyse price data. Although the main maize harvest is often in May-June, food becomes available sooner than this as small grains and early-planted maize are harvested, and as consumption of green maize from the field takes place. This choice of April as the beginning of the year thus enables agricultural statistics and growth monitoring information to be compared.

The second stage in the preparation of nutritional status data was the treatment of missing values. These 'missing' values occur where a district hospital has failed to complete a T5 form for a particular month and so no growth monitoring statistics are available. This

occurs frequently in the Zimbabwean data set and clearly affects the calculation of annual weight-for-age malnutrition rates. As described in Chapter 4, the prevalence of under-nutrition varies by season, with the highest rates occurring immediately pre-harvest between January and March. This would mean, for example, that if a year was missing one month's data from February, simply calculating percentage under-nutrition from the remaining eleven months would probably lead to an under-estimate of the annual total because of this seasonal variability. Consequently, 'missing' values were replaced with the moving average, based on the following and preceding months' figures. This reduced the problem of missing data, although no annual malnutrition rates were calculated for years with more than two months of missing data.

To look at year-to-year variation, a simple differencing technique was used, in which the percentage of under-nourished children in the previous year was subtracted from the percentage for each year. The result of this calculation (sometimes known as 'first differencing') was positive when percentage under-nutrition had increased and negative when it had decreased. These differences were calculated for the year 1989/90 through to 1992/93¹.

6.2.2 Indicators of nutritional vulnerability

As noted in Chapter 5, the assessment of factors likely to influence prevalence of under-nutrition is restricted by limited data availability. For annual analyses, this problem is even more pronounced, since even less information is collected on a yearly basis. However, seven indicators can be identified that reflect some of the potential causes of under-nutrition, as shown in table 6.1. Each of these is discussed in greater detail below.

¹ Calculation of first differences for other years was not possible because of gaps in the T5 records obtained from the Ministry of Health.

Indicator	Reason for Use	Source
Change in maize yield per district since last year	Reflects food availability	Agritex & National Early Warning System
Change in goat numbers since last year	Reflects food availability, source of income	Department of Veterinary Services
Change in cattle numbers since last year	Reflects food availability, source of income	Department of Veterinary Services
Change in total rainfall since last year	Affects health status through water supplies and food access through agricultural production	Meteorological Department
Change in proportion of population under 5 years reporting Acute Respiratory Infection at health centres	Reflects impact of health status on nutrition.	Ministry of Health, Central Statistical Office
Change in proportion of population under 5 years reporting diarrhoea at health centres	Reflects impact of health status on nutrition.	Ministry of Health, Central Statistical Office
Change in proportion of population requesting drought relief from government	Indicates the extent to which communities are failing to obtain sufficient food	Department of Social Welfare, Central Statistical Office

Table 6.1: Annual indicators of nutritional insecurity from available secondary data

6.2.3 Arable production:

As Table 6.2 shows, yields of the crops monitored by Agritex are well correlated with one another. This strong correlation between yields holds true even after the factors representing the district characteristics are taken into account². Yields of one crop (maize, the most important source of staples) were chosen to represent agricultural output, primarily because maize is the principle staple in Zimbabwe but also because its yields are well correlated with those of other crops. Yields were chosen as an indicator rather than the area under maize, because the total arable area planted is known to vary very little from one year to the next (Hutchinson, 1991). Mean maize yields for each district for 1987-1992 were calculated based on the mean of the constituent Communal Areas, weighted by the area planted. Once these had been calculated, the previous year's yield was subtracted from the figure for each year to give the change in maize yields.

² The influence of district characteristics was taken into account by calculating partial correlation coefficients.

Crop	Mhunga	Maize	Sorghum	Sun-flower	Rapoko	beans
Ground-nuts	0.63 (254)	0.64 (307)	0.41 (328)	0.71 (325)	0.64 (304)	0.49 (139)
Mhunga		0.50 (256)	0.47 (252)	0.61 (255)	0.71 (241)	0.38 (95)
Maize			0.38 (309)	0.66 (324)	0.64 (308)	0.41 (139)
Sorghum				0.44 (308)	0.40 (289)	0.26 (132)
Sun-flower					0.70 (304)	0.40 (140)
Rapoko						0.44 (140)

Table 6.2: Correlation co-efficients (R) for annual district crop yields reported by Agritex under the National Early Warning System (all correlations are significant at the 99% level; figures in brackets indicate the number of observations or district-years recorded)

6.2.4 Livestock numbers

The size of the goat and cattle populations was calculated by district for the period 1987-1992. Livestock census figures were aggregated to district level, using statistics for those reporting areas that could be located. Many sub-district units reported animal numbers for one or two years only, so only those units which reported cattle and goat numbers regularly were chosen to be representative of each district. For some districts (notably Tsholotsho and Kariba), it proved impossible to identify consistent reporting units, so no livestock figures were compiled for such areas. Elsewhere, most of the statistics used in the district totals were for either Communal Areas or the SSCFA, as resettlement areas generally reported livestock numbers very sporadically.

6.2.5 Rainfall data:

In addition to maize yields and livestock, changes in rainfall were also considered in relation to levels of child under-nutrition. Annual rainfall was included as well as the communal sector agricultural indicators already discussed because of its effect on availability of water sources and commercial farming, an important source of employment not covered by these agricultural statistics. Only the annual total rainfall was considered, although rainfall distribution is undoubtedly important for crop growth as well. The Zimbabwean newspaper the Herald (1994a, 1994b), for example, reported how plentiful early rains in 1994/95 were followed by a late dry spell that devastated maize crops.

In order to facilitate comparison with the growth monitoring statistics that were organised by district, a rainfall map had to be interpolated from measurements at meteorological stations. This interpolation was necessary because the network of meteorological stations is concentrated in Mashonaland West and some districts do not contain any meteorological stations. A co-kriging technique (Bogaert *et al.*, 1995) was used to interpolate rainfall values over a regular grid across Zimbabwe. Two additional data sets, elevation and Cold Cloud Duration (CCD) were used to guide the interpolation process. CCD is a satellite-derived measure of the duration of cumulonimbus (thunderstorm clouds), and thus the amount of convectional rainfall falling in a given area. This technique is described in more detail in Appendix 3. Once this interpolated rainfall surface had been created, it was overlaid on a district boundary map within a GIS and mean total annual rainfall for each district was calculated.

6.2.6 Demand for drought relief

The proportion of the population in each district requesting drought relief was calculated using Department of Social Welfare (DSW) statistics and population figures from the 1992 census (Government of Zimbabwe, 1994c; Government of Zimbabwe, 1993d). Where one or two months' figures for previews had not been entered in the DSW records, these were estimated from a moving average based on the preceding and following months' figures. This enabled annual demand for drought relief to be calculated. Prior to 1992, estimates of total population needed to account for population growth in the years leading up to the census. Unfortunately, calculation of sub-national population growth rates was not possible, because all provincial and almost all district boundaries changed between the 1982 census and the 1992 census (Government of Zimbabwe, 1985; 1994e). Consequently, the national demographic growth rate of 3.13% per year was used to adjust the 1992 district population totals retrospectively and estimate the size of the population in earlier years. This application of a national growth rate follows the approach adopted by Government of Zimbabwe (1994c).

6.2.7 Health Data

As well as reporting the prevalence of under-weight children under 5 years, the National Health Information System (NHIS) also reports the number of children in this age group who present themselves at health centres with different diseases. Although many

different diseases are reported, this analysis concentrates on diarrhoea and acute respiratory infections (ARI). This is because both these complaints are known to affect nutritional status (Khan and Ahmad, 1986; Rowland *et al.*, 1988) and because they affect large numbers of young children every year. In addition, reported cases of the two complaints are not correlated, suggesting that they may affect nutritional status at different times and in different areas and should thus be considered separately in a model of its causes. Clearly, one of the main weaknesses of the NHIS data as indicators is the problem of under-reporting. Not all children with ARI or diarrhoea are likely to visit health centres, and the pattern of attendance may vary spatially and between years (see Chapter 3). As with the growth monitoring data, where a district had not returned figures for the number of under-5s with diarrhoea or ARI for one or two months, the number of cases was estimated using a moving average technique. The total number of cases reported in each year between 1988 and 1993 was then calculated. The proportion of the population under 5 years attending health centres with the two complaints was estimated based on the results of the 1992 census, adjusted for population growth (see the discussion of demand for drought relief).

6.3 *Yearly analysis*

6.3.1 Methodology:

There have been relatively few documented attempts at either yearly analysis or forecasting of changes in under-nutrition prevalence described in the literature (Mason *et al.*, 1987; Brooks *et al.*, 1985). Mason *et al.* (1987) devised an annual forecasting system based on the proportion of children underweight in Botswanan health regions, whilst Brooks *et al.* (1985) devised a similar system for Indonesia. Mason *et al.* (1987) devised their forecasting system by dividing both prevalence data and values of predictors for each district-year into two categories, high or low. Cut-off points for both predictors and prevalence data were chosen so as to maximise the effectiveness of the prediction system. The Botswanan system examined the predictive power of a livestock index and a maize index between 1978 and 1983, whilst the Indonesian system considered variables such as the percentage of rice area harvested.

Two features of the work by Mason *et al.* (1987) restrict its usefulness for exploring the relationship between underweight prevalence and indicators. Firstly, the approach ignores the problem of non-stationarity in the data (this refers to the problem of the mean

and variance of a series changing over time). For example, there could be a trend towards lower rainfall at the same time as a trend towards lower under-nutrition prevalence, but the two trends may not be related. Some means of eliminating trends from the data used is therefore required, but this was not attempted in their study. Secondly, their work provides no methodology for selecting cut-off points, other than visual inspection of a scatterplot of the district-years' data. For these reasons an alternative approach was adopted.

The alternative methodology is to compare the *change* in the value of an indicator with the change in underweight prevalence. This process of subtracting one year's figures from those in the previous year provides a means of dealing with non-stationarity in time series data (SPSS Inc, 1993: pp 619-621). This also resolves the problem of selecting cut-off points, since observations can either be classified as increasing or decreasing. However, one consequence of adopting this technique is that it reduces the number of observations available for analysis. This is because two values are required in order to calculate the magnitude of changes: the current value and the value for the previous year. If *either* value is unavailable, then the observation cannot be included in the analysis.

The direction of change relative to the previous year was calculated for all the indicators described above and for the percentage of under-weight children. In this respect, the methodology adopted follows the 'convergence of indicators' approach to assessing changes in under-nutrition prevalence described by Kelly (1992). In this approach, the direction of change of indicators is used rather than their absolute value. When several indicators all show the same direction of change, this is taken as a sign of impending nutritional crisis. However, Kelly (1992) notes that this procedure is often a 'rule of thumb' or heuristic, rather than a statistically calibrated approach to nutritional forecasting.

Here, the direction of change of each indicator was cross-tabulated against change in underweight prevalence initially. The change in each indicator was compared with under-nutrition prevalence through a chi-squared test. As noted in Chapter 5, the prevalence of underweight children declined in most districts over the period 1988-1993. Consequently, in many years very few districts experienced an increase in underweight prevalence. Since the low cell frequencies made a separate chi square analysis for each year invalid, data from all years were pooled and examined together. Following this bivariate analysis, it was intended that the interaction ('convergence') of different indicators could be investigated subsequently. In addition, correlation coefficients were calculated for the change in each

indicator compared to the change in underweight prevalence to confirm the results of this analysis.

6.3.2 Results and Discussion

Correlation coefficients for the change in the indicators with change in underweight prevalence are given in Table 6.3. This analysis suggested a significant relationship between three indicators and change in underweight prevalence. Changes in maize yields and rainfall were both negatively correlated with levels of under-nutrition, whilst the proportion of the population in each district requesting drought relief was positively correlated with the change in percentage underweight.

Indicator – change in:	Pearson's correlation coefficient	Number of observations
Precipitation	-0.24 (**)	228
Cattle numbers	0.07	114
Reported cases of diarrhoea in children under 5 years	-0.07	168
Reported cases of acute respiratory infection in children under 5 years	0.10	168
Goat numbers	0.03	114
Maize yield	-0.18 (**)	212
Proportion of population requesting drought relief	0.15 (*)	172

Table 6.3: Correlation coefficients for change in selected indicators and change in annual underweight prevalence in Zimbabwean districts, 1988-1995 (** indicates coefficient significant at the 99% level; * indicates coefficient significant at the 95% level)

The full results from the cross-tabulation of annual indicators with prevalence data are given in Appendix 4. The only indicator that was significantly related to changes in under-nutrition rates (at the 95% level) was rainfall, as shown in Table 6.4 below. Rainfall increases were relatively rare in the Zimbabwean districts between 1987 and 1992. When rainfall did increase, the under-nutrition rate for the following year fell in three-quarters of the cases examined. A scatter-plot of precipitation and rainfall is also shown in Figure 6.1. The outlying value showing a particularly large decrease in under-nutrition of 9% is for Binga district, which experienced a rapid improvement in child nutritional status.

Rainfall / Malnutrition	DECREASE	INCREASE	Total
DECREASE	81 (89.6)	85 (76.4)	166 (72.8%)
INCREASE	42 (33.4)	20 (28.6)	62 (27.2%)
Total:	123 (53.9%)	105 (46.1%)	228

Table 6.4: *Changes in rainfall compared to changes in percentage weight-for-age malnutrition in children under 5 for 57 Zimbabwean districts, 1988-1993 (figures in brackets indicate the expected number of district-years in a category).*

The probability of an increase in under-nutrition prevalence occurring rises from 19% where rainfall increases to 34% when rainfall decreases, suggesting this has been related to higher under-nutrition during the period considered. Since this bivariate analysis suggested that none of the other indicators apart from rainfall were related to nutritional status, no attempt was made to examine the interactions (or 'convergence') between the different indicators.

There are several reasons why changes in malnutrition rates may be more related to rainfall than the agricultural variables such as maize yields:

- Firstly, there are several other linkages - apart from the size of the communal maize harvest and livestock herds - between rainfall and under-nutrition rates. The commercial sector, although practising irrigation to a much greater extent, is also affected by drought and a drought year on the commercial farms reduces employment prospects for many of the poorer sections of society. Exceptionally bad drought years have also been associated with cattle mortality, asset sales and with lowering of the water table and consequent loss of water sources.
- Secondly, rainfall data may be more accurate than the agricultural indicators, since it is generally easier to assess levels of precipitation than the size of the maize harvest, for example. Several reasons for expecting the quality of agricultural data, particularly livestock data, to be poor have already been suggested in Chapter 2.

However, this finding differs from another study in Zimbabwe, which sought to forecast crop production from satellite-derived sea surface temperatures. Cane *et al.* (1994) found a higher correlation between sea surface temperatures and subsequent maize yields in Zimbabwe than with subsequent rainfall over the country. This finding suggests that the first explanation above, rather than poorer data quality in crop production statistics, may explain the stronger relationship with rainfall found here.

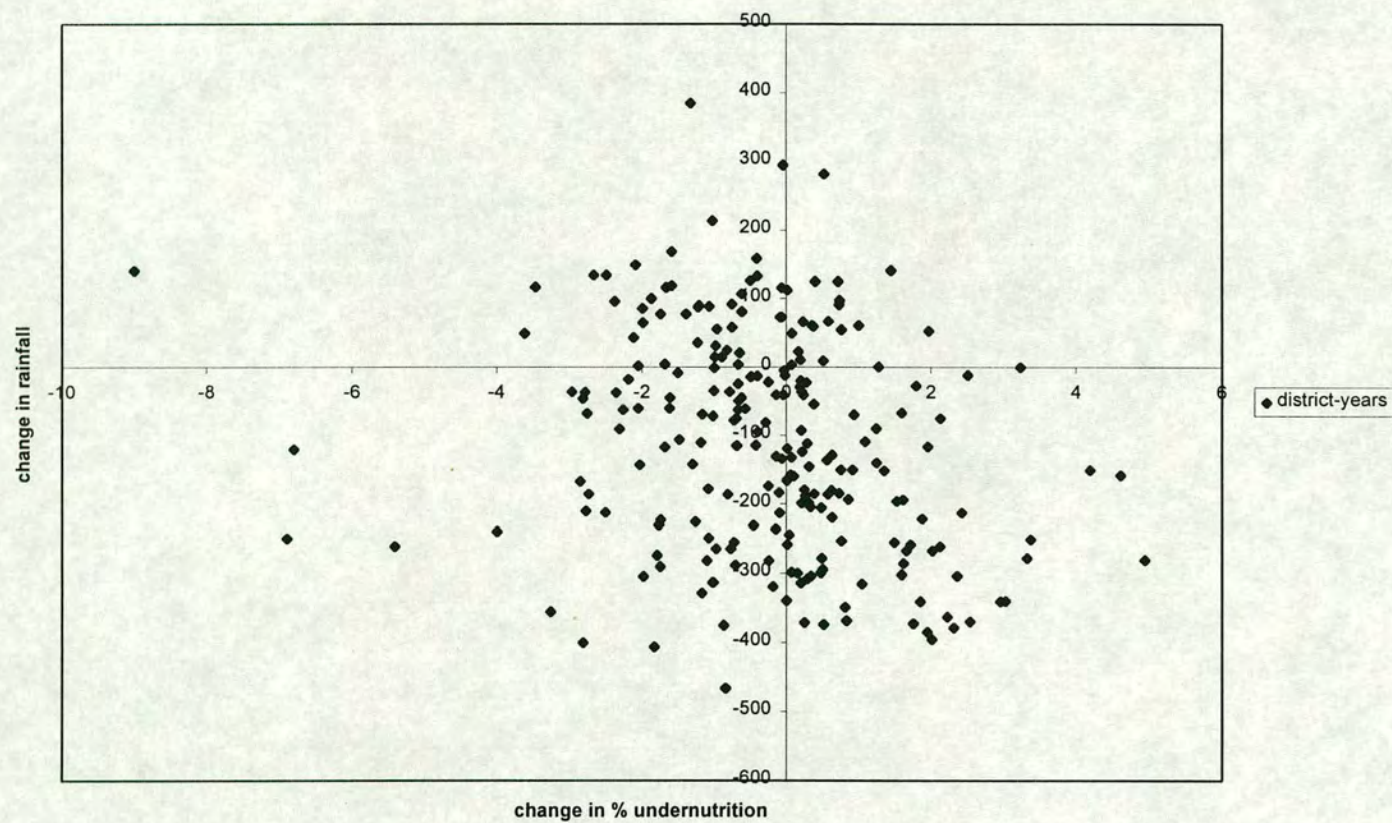


Figure 6.1: Scatterplot of change in annual rainfall against change in % under-nutrition for Zimbabwean districts for 1988-1993.

6.4 Monthly Analysis

6.4.1 Methodology

The annual analysis of underweight prevalence was restricted by the paucity of indicators available on an annual basis. For a monthly analysis, the number of indicators is even more restricted, since very few data sets are collected monthly. As Chapter 2 indicated, the only data sets consistently compiled on a monthly basis are reported cases of diseases, rainfall and satellite-based indicators such as NDVI and CCD. In the case of rainfall and the satellite-based indicators, these are largely inappropriate for the dry season between May and August, when virtually no rain falls in Zimbabwe. Consequently, monthly analysis was restricted to the relationship between reported cases of diseases and underweight prevalence. In addition to acute respiratory disease and diarrhoea, malaria was also chosen as a third common disease likely to affect the nutritional status of children as described in McGregor (1982).

Monthly analysis of the data is further complicated by the presence of seasonality, in addition to the effects of long-term trends discussed earlier. In Chapter 4, for example, it was found that the proportion of children underweight increased during the January-March period. As with long-term trends, the fact that two series have similar seasonal peaks does not necessarily mean that they are directly related. Consequently, reported cases of disease and underweight prevalence data were seasonally differenced to reduce the confounding effects of seasonality and long-term trends (SPSS Inc, 1993: p. 621). This involves subtracting the value twelve months previously from each observation in a time series.

Once seasonal differencing had taken place, cross-correlation was used to analyse the relationship between underweight prevalence and reported cases of the three diseases for each district. Cross-correlation is a technique used to examine the strength of the relationship between two time series at different lags. Correlation co-efficients for the two series are calculated for a range of lags to identify the relative lag at which the two series are most strongly correlated. This technique has also been used to examine the relationship between measles cases in one area and measles cases in a second area. Such analyses have been undertaken for states of the USA and different African countries (Cliff *et al.*, 1992; Cliff *et al.*, 1993) and influenza cases in different districts of Iceland (Cliff *et al.*, 1986). In

the Iceland study, for example, peaks in reported cases of measles in remote rural districts were found to lag behind cases in the capital and a major port.

This technique was used here both at national and district level. At national level, six districts (including the main urban centres of Harare and Bulawayo) had no data on reported disease cases for 1995. Consequently, quasi-national, aggregate disease statistics were produced based on 51 out of the 57 districts in the country to maximise the length of the time series available for analysis. The technique was also applied to disease cases and under-nutrition prevalence for all 57 districts in Zimbabwe individually. The aim of replicating this same analysis across all districts was to identify whether a consistent pattern of lags and cross-correlation would emerge in all parts of the country, following the methodology of Cliff *et al.* (1986). Time series and cross-correlation plots were examined for each district. Reported cases of the three diseases were classified as either positively correlated with percentage underweight, negatively correlated, uncorrelated, or showing a mixture of both positive and negative correlation depending on the lag considered. In addition, a summary average lead/lag statistic was calculated for each district based on all the lags showing significant correlation (at the 95% level) with under-nutrition rates based on the formula:

$$L_j = (\sum_s k_s / R_s) / (\sum_s 1 / R_s) \quad (1)$$

{where R_s = rank of s biggest correlation of district j and reference district;

L_j = average lead/lag statistic for a given district i ;

k_s = lead or lag of s th biggest correlation of district j and reference district.}

(source: Cliff *et al.*, 1986: p.195)

6.4.2 Results and Discussion

Figure 6.2 shows the results of the national level cross-correlation analysis with under-nutrition rates. The cross-correlation analysis suggested that there was no correlation between reported malaria cases and the proportion of children who were underweight. Similarly, the analysis suggested a slight negative correlation between underweight prevalence and cases of respiratory infection four to five months earlier. However, the

cross-correlation for reported cases of diarrhoea suggested that this varied much more closely with underweight prevalence, once long-term trends and seasonality had been taken into account. The proportion of underweight children was particularly well correlated with reported cases of diarrhoea during the same month and during the previous month ($R = 0.487$). Visual inspection of changes in the two variables over time suggested that there had been high levels of both underweight prevalence and reported diarrhoea cases early in 1988, followed by a return to the long-term trend. In late 1992 and early 1993, under-nutrition and reported cases of diarrhoea both increased and then returned back to follow the long-term trend in early 1994. This broad movement of the two variables in tandem, once long-term trends and seasonality have been accounted for, appears to be the reason for the strong correlation between the two.

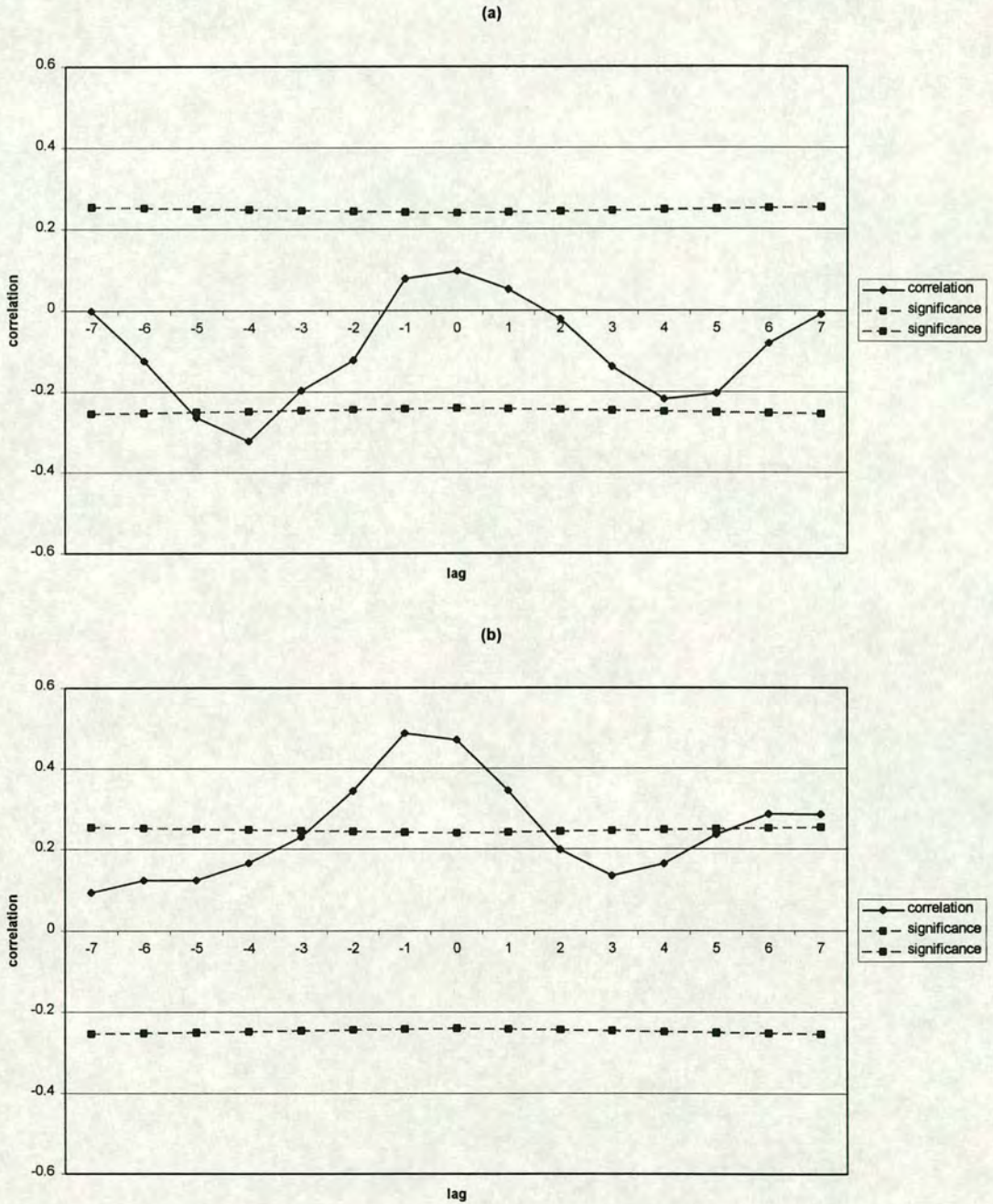


Figure 6.2: (a) Cross-correlation for reported cases of Acute Respiratory Infection in children under 5 years with the percentage of underweight children under 5 years for 51 Zimbabwean districts, 1988-1995; (b) Cross-correlation for reported cases of diarrhoea in children under 5 years with the percentage of underweight children under 5 years for 51 Zimbabwean districts, 1988-1995 (lags are given in months; lines depict significance at the 95% level).

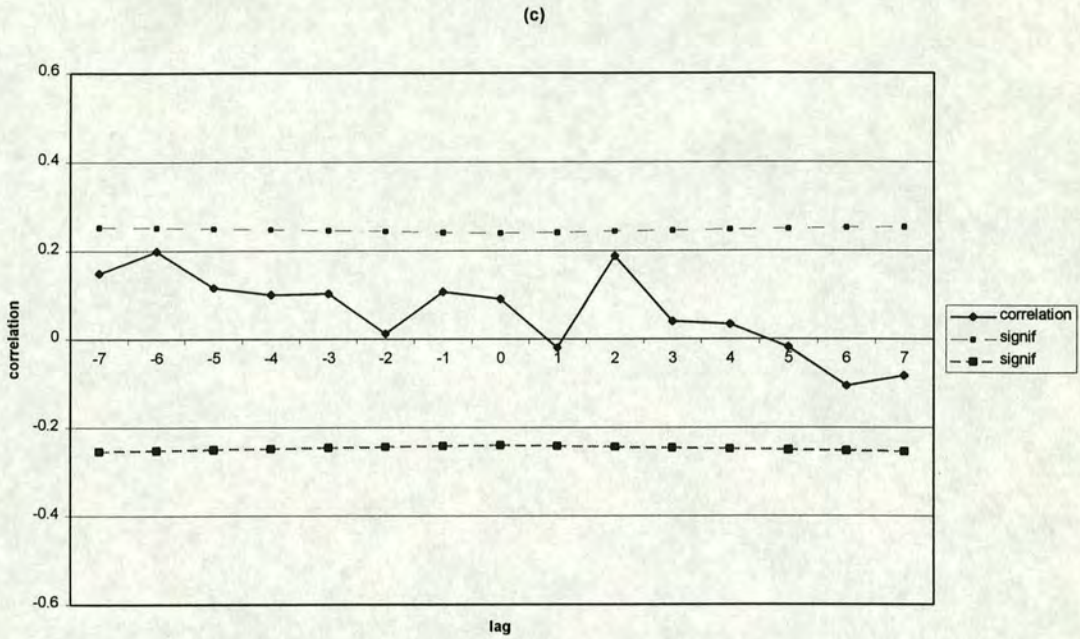


Figure 6.2: (c) Cross-correlation for reported cases of malaria in children under 5 years with the percentage of underweight children under 5 years for 51 Zimbabwean districts, 1988-1995

Table 6.5 summarises the results of the cross-correlation analysis at district level – full district-level results are given in Appendix 5. Districts showing positive correlation between under-nutrition prevalence and reported disease cases have been further subdivided into those with short average lead/lag statistics and those with longer average lead/lag statistics. For reported diarrhoea cases, almost half of the Zimbabwean districts showed positive correlation and short average lead/lags with underweight prevalence, suggesting that the two phenomena vary in tandem in many parts of the country. In contrast, reported malaria cases were uncorrelated with underweight prevalence in 24 districts, suggesting little relationship between malaria and under-nutrition prevalence at the population level. For Acute Respiratory Infections, there was negative correlation with the percentage of underweight children recorded in almost half the districts.

Type	Diarrhoea	Malaria	ARI	Total
No correlation	12	24	14	41
Negative correlation	6	11	24	41
Both positive & negative correlation	3	8	5	16
Positive correlation (average lead/lag ≤ 2 months)	25	9	7	41
Positive correlation (average lead/lag > 2 months)	12	6	8	26
Total	58	58	58	174

Table 6.5: results of cross-correlation analysis of reported cases of malaria, diarrhoea, and ARI with underweight prevalence for 58 Zimbabwean districts (figures in each cell indicate the number of districts displaying the characteristic concerned).

6.5 Forecasting of Under-Nutrition Prevalence

6.5.1 Methodology:

The annual analysis of under-nutrition rates suggested that rainfall data could be used to forecast changes in the underweight prevalence, whilst the monthly analysis suggested that diarrhoea cases might be a useful predictor. Clearly, an annual forecasting system would be of more use, since it would give more time for action to be taken to alleviate nutritional problems. An annual system would forecast changes a year in advance, whereas the cross-correlation analysis of national prevalence data suggested that under-nutrition levels could only be forecast a month in advance from reported diarrhoea cases. However, as developed here, an annual prediction system would be less precise than a monthly system. The annual analysis predicts only the direction of change in prevalence (higher or lower), whereas the monthly analysis could predict both direction and magnitude of change. A technique commonly used to evaluate the effectiveness of a forecasting system is to divide the existing data set into two parts: a calibration data set and a test data set (SPSS Inc, 1990). This proved difficult in the case of the annual prevalence data, since the number of observations available was small and further sub-division of the data set would invalidate the chi-square statistic used. Critically, no rainfall data were available for 1994 despite a search of four different sources of meteorological data (see Chapter 2) and this prevented an assessment of forecasting effectiveness after 1993.

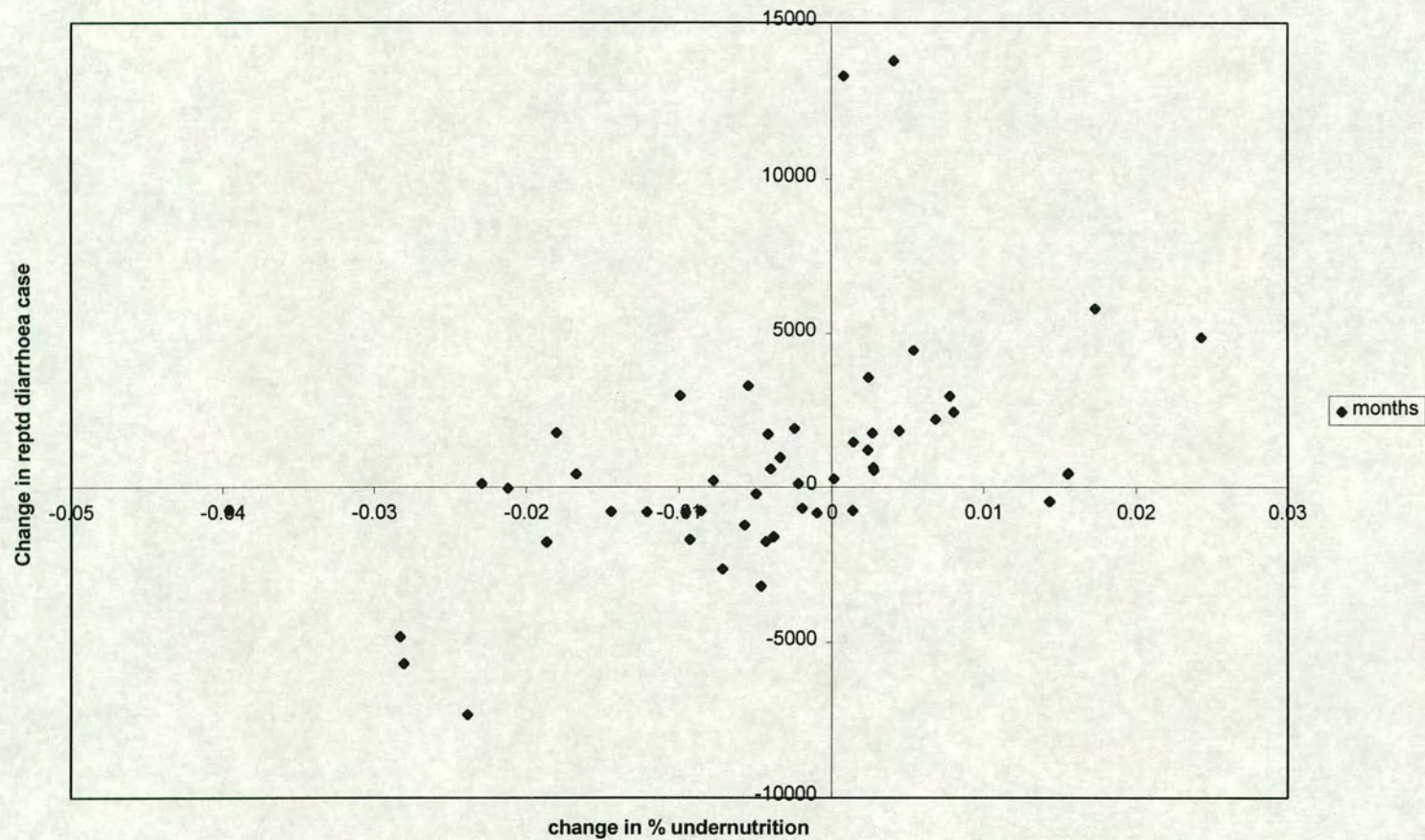


Figure 6.3: scatterplot of seasonal change in percentage underweight and reported cases of diarrhoea among children under 5 years one month earlier. Figures are monthly for Zimbabwe as a whole during 1988-1995.

However, there was greater scope for evaluating the effectiveness of a monthly forecasting system. Figure 6.2b suggested that the number of diarrhoea cases one month prior to the current month might be a useful predictor (or leading indicator) of a change in the malnutrition rate. This suggestion is also borne out by Figure 6.3, which shows a scatterplot of the change in under-nutrition against the change in reported cases of diarrhoea amongst children under 5 years one month earlier. To investigate this relationship further, a simple forecasting system was developed which used the previous month's under-nutrition rate and the change in the number of reported cases of diarrhoea amongst children under 5 years to predict the current under-nutrition rate. For this purpose, the national time series of reported cases of diarrhoea and percentage under-nutrition was sub-divided into a prediction data set and a validation data set. The data set was split in two different ways to examine how this division might affect the analysis. In the first case, data prior to 1992 were used to calibrate the forecasting system and data from 1992 onwards to test it. In the second case, the calibration data set was extended until the end of 1992 to include the impact of the 1991/1992 drought.

One of the standard assumptions of linear regression is that error terms are uncorrelated with one another (Hair *et al.*, 1995: p. 69). However, in the case of time series data, this assumption is frequently violated. Consequently, a Durban-Watson statistic was calculated in SPSS to test for serial correlation of error terms in the national data set. A value of 0.64 suggested that the error terms in the equation were correlated³, so a partial autocorrelation function was calculated for the time series. This function shows the correlation between values of a series at different times after the effects of the intervening times have been removed. This suggested that correlation existed only at a lag-time of one month, so the auto-regression procedure AREG in SPSS was used to account for first-order autocorrelation of the error term. The method of exact maximum likelihood was used to parameterise a model that predicted the current month's prevalence from the previous month's prevalence and reported diarrhoea cases amongst children under 5 years.

³ A value less than 2 for the Durban-Watson statistic indicates positive serial autocorrelation of the error term in a regression equation.

6.5.2 Results:

Table 6.6 shows the results of fitting the regression model to the national prevalence data. The model for 1988-1991 was based on 35 observations and had an adjusted R^2 of 0.967, whilst that for 1988-1992 was based on 47 observations and had an adjusted R^2 of 0.976. For both models, the positive co-efficients for the previous month's underweight prevalence and reported diarrhoea cases were both significant, suggesting that both had predictive value. Table 6.7 gives an analysis of the error term for the 'test' data set, which was for the period 1992-1995 for the first model and 1993-1995 for the second model. In both cases, the mean error term is close to zero, suggesting that neither model seriously under- or over-estimates prevalence during the validation period. This is confirmed by Figure 6.4, which shows the predicted and actual national prevalence data for both models over the period 1988-1995. Generally, both models match the observed data quite well but did not forecast the most important events – increases in underweight prevalence – during the validation period. The monthly forecasting model calibrated between 1988 and 1991 failed to predict the two major increases in underweight prevalence in late 1992 and late 1995. The forecasting model calibrated between 1988 and 1992 similarly failed to predict the increase in under-nutrition in late 1995.

Model	Independent variable	Co-efficient
Based on 1988-1991	Previous month's underweight prevalence	0.65 (**)
Based on 1988-1991	Previous month's reported diarrhoea cases	0.000002 (*)
Based on 1988-1991	Constant	-0.0082 (*)
Based on 1988-1992	Previous month's underweight prevalence	0.76 (**)
Based on 1988-1992	Previous month's reported diarrhoea cases	0.000002 (**)
Based on 1988-1992	Constant	-0.0047 (n.s.)

Table 6.6: statistics for linear regression of previous month's reported diarrhoea cases and underweight prevalence on current month's national underweight prevalence (** indicates co-efficient significant at the 99% level; * indicates co-efficient significant at the 95% level; n.s. indicates an insignificant co-efficient.)

Calibration data used in model	'Goodness of fit' statistic	Value
1988-1991	Mean error (calibration period)	0.000
1988-1991	Root Mean Square error (calibration period)	0.007
1988-1991	Mean error (test period)	0.007
1988-1991	Root Mean Square error (test period)	0.009
1988-1992	Mean error (calibration period)	0.000
1988-1992	Root Mean Square error (calibration period)	0.007
1988-1992	Mean error (test period)	-0.002
1988-1992	Root Mean Square error (test period)	0.009

Table 6.7: Analysis of 'goodness of fit' for calibration period versus validation period for two regression models forecasting change in national underweight prevalence

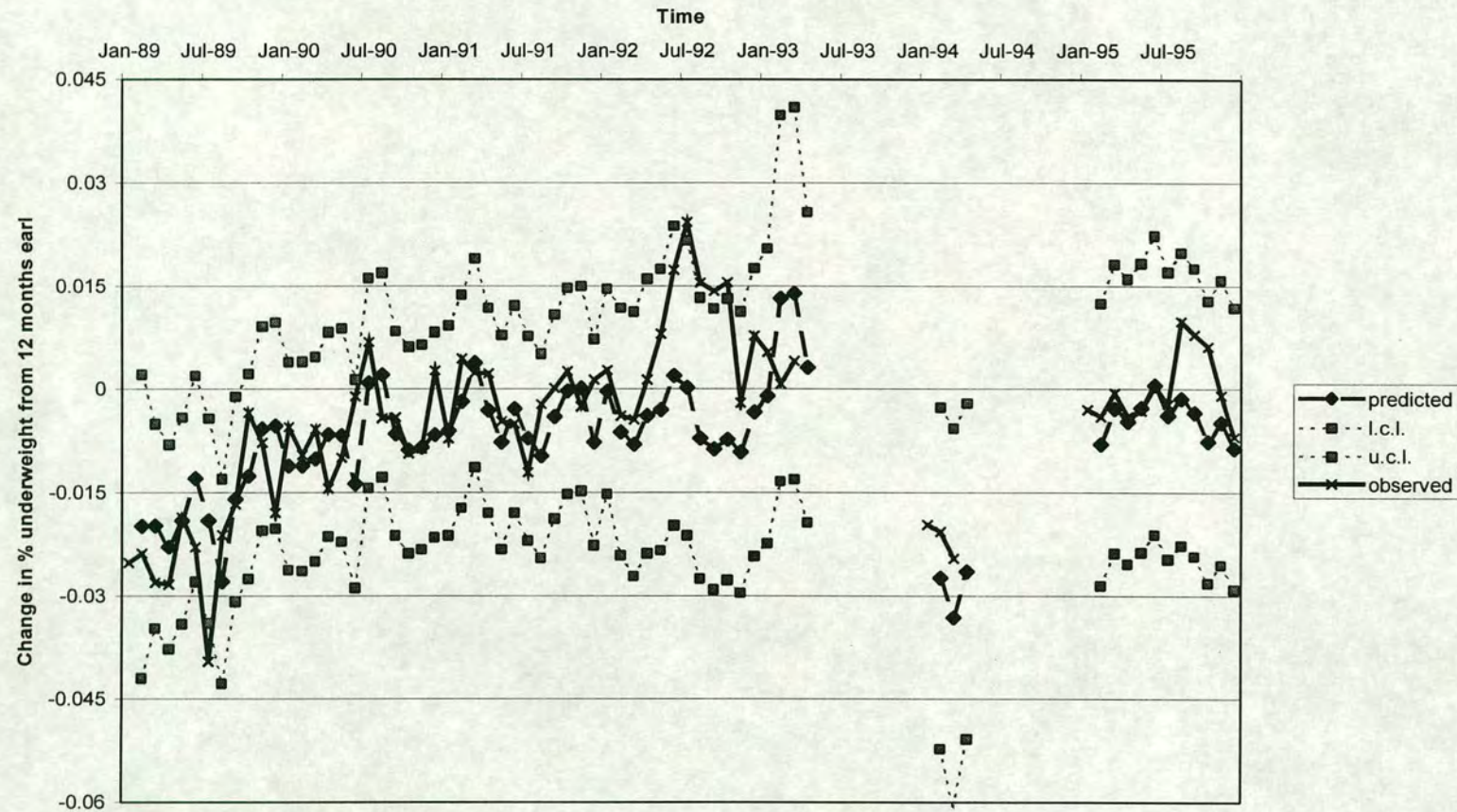


Figure 6.4 (a): Forecast and observed change in prevalence of underweight among children under 5 years, 1989-1995 (l.c.l. = lower confidence limit of prediction; u.c.l. = upper confidence limit of prediction. Changes shown are absolute, relative to prevalence 12 months previously. Predictions are calibrated from data for 1988-1991)

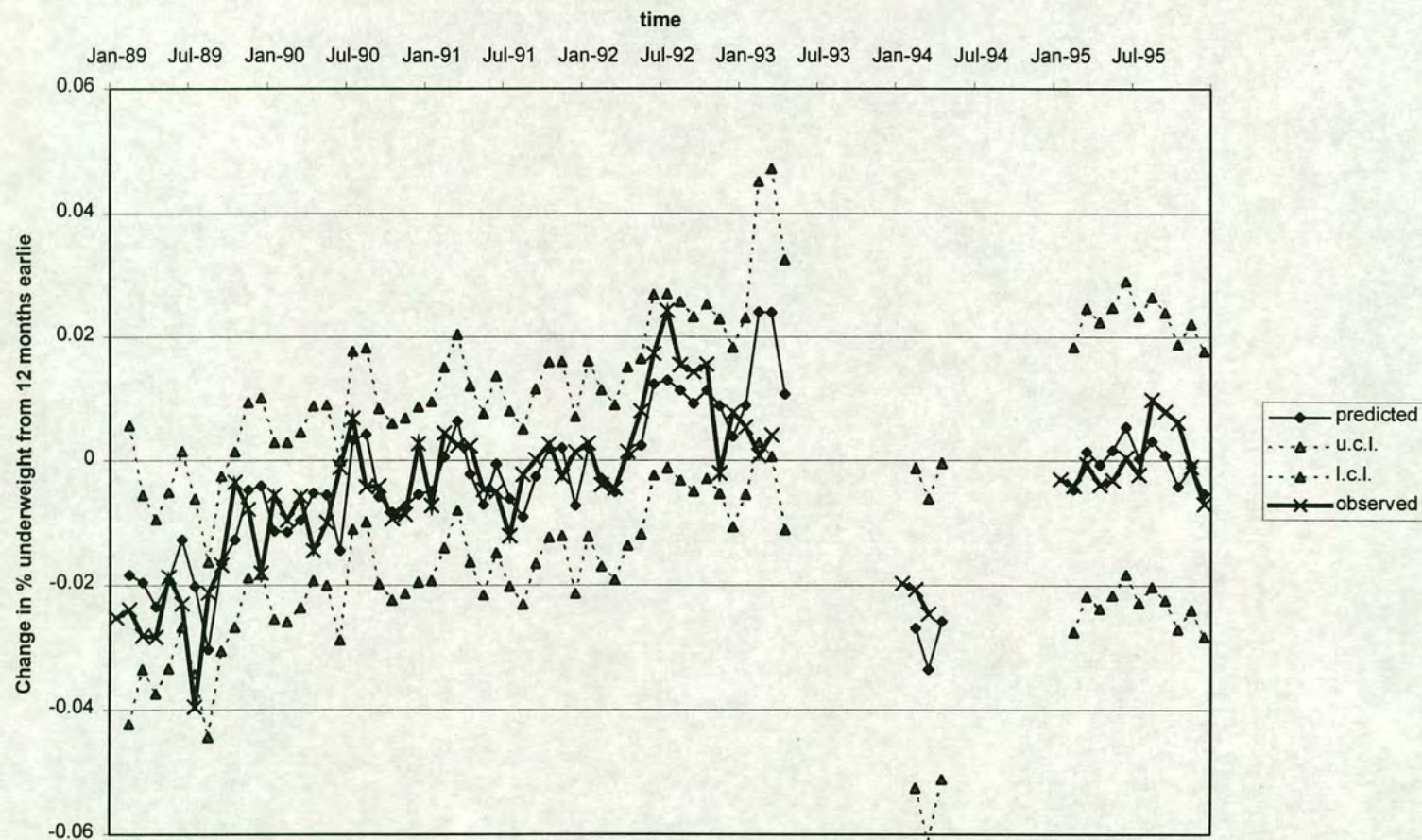


Figure 6.4 (b): Forecast and observed change in prevalence of underweight among children under 5 years, 1989-1995 (l.c.l. = lower confidence limit of prediction; u.c.l. = upper confidence limit of prediction. Changes shown are absolute, relative to prevalence 12 months previously. Predictions are calibrated from data for 1988-1992)

6.5.3 Discussion:

The monthly analysis confirms that there is a close association between the percentage of underweight children and reported diarrhoea cases. However, in practical terms the monthly forecasting system developed is of relatively little use, since it can only forecast under-nutrition rates one month in advance. Furthermore, despite successfully predicting the decrease in under-nutrition in early 1994, neither of these models was able to detect the main increases in underweight prevalence during the validation period, which occurred in late 1992 and late 1995. Such increases in percentage underweight are clearly of more concern than nutritional improvements. The same problem occurs with the annual rainfall data, since a decrease in rainfall is followed by an increase in under-nutrition in only 34% of cases. This inability to predict increases in under-nutrition may be because of problems of data quality. Burrough (1986) suggests that differencing greatly increases the relative magnitude of data set errors and both forecasting systems described here are based on differenced data.

There are further reasons for doubting the usefulness of the two methods developed here for forecasting. In particular, Zimbabwe's economy and society have been affected by numerous changes since 1995, which may change the patterns of under-nutrition found in the time series here. For example, the impact of drought in the past has been mitigated by the Drought Relief Programme providing grain to large numbers of rural households (Marquette, 1997). This system was reformed in June 1995 (towards the end of the time series used here) and replaced with a Grain Loan Programme (The Herald, 1995b). However, the system only really became operational during late 1995 because of transport difficulties and so its effects are not apparent in the time series used here (FEWS, 1995). Thus, the system of grain provision that operated for virtually all of the time series used for forecasting has changed and may be further revised again, altering the nutritional impact of drought. The impact of drought may also be increased in future by the further removal of government support for the Grain Marketing Board (GMB), which used to guarantee high prices for grain producers and subsidised prices for grain consumers. In December 1997, for example, a 21% increase in the price of maize meal led to food riots in Harare, forcing the government to intervene to stabilise prices (FEWS, 1998). Such large changes in consumer grain prices did not occur during the period used for forecasting here, since the GMB was able to set grain prices for the season in advance. Other major changes since 1995 likely to affect

under-nutrition rates include the government's land reform programme, which aims to acquire land forcibly from commercial farmers, and the increasing impact of HIV/AIDS.

Thus, the two forecasting methods derived here – based on rainfall and reported diarrhoea cases respectively – have limited use. Neither is able to predict increases in under-nutrition with great accuracy and socio-economic conditions in Zimbabwe have changed considerably since 1988-1995, the period used to calibrate the two forecasting models.

6.6 Conclusions:

Analysis of changes in annual malnutrition patterns gave some indication that changes can be explained using secondary data. The 'goodness of fit' is low, although this is only to be expected with differenced data. Several variables – changes in the proportion of under-5s suffering two major complaints (diarrhoea and respiratory infection) and changes in goat and cattle populations – appear to be unrelated to malnutrition patterns. This may, however, be because of problems of data quality and not reflect the true pattern of change. Three variables – change in total rainfall, the change in the proportion of population requesting drought relief and changes in maize yields – were significantly correlated with under-nutrition rates, but explained only a small proportion of overall variability. Simple categorical analysis suggested that only changes in rainfall were related to changes in underweight prevalence on a year-by-year basis. When rainfall increased, levels of under-nutrition generally decreased in the following year, which is consistent with expectations. However, the strength of the relationship even between rainfall and under-nutrition was weak, whilst the other indicators were found to be unrelated to under-nutrition prevalence as recorded through the growth monitoring scheme. One reason for this may be the quality of data from the growth monitoring scheme. Attendance was found to vary both over time and between districts in Chapter 3. Although prevalence rates from growth monitoring data were well correlated with an independent, cross-sectional survey at province level, data from the scheme may give only a poor picture of year-to-year district level changes because of variability in attendance. Thus, the limitations of the growth monitoring data may also explain why there is no apparent relationship between the percentage of underweight and the majority of indicators considered here.

Monthly analysis was also undertaken to assess the relationship between reported

disease cases in children under 5 years and the percentage of underweight children. Cross-correlation analysis of national statistics suggested that the proportion of underweight children varied with reported cases of diarrhoea, once long-term trends and seasonality had been accounted for. District-level data were somewhat harder to interpret, but supported the aggregate, national picture. Most districts showed positive correlation between reported diarrhoea cases and under-nutrition rates. There was also some weaker evidence at district level of negative correlation between acute respiratory infection cases and under-nutrition.

Both monthly and yearly findings are consistent with the model of the causes of under-nutrition (described in Section 1.2), taking account of the accuracy of the various indicators. Lower rainfall seems likely to lead to higher levels of under-nutrition through reduced food access, whilst diarrhoea is likely to cause growth faltering in children. Reported cases of diseases like diarrhoea are easily integrated with nutritional prevalence data, since they are collected through the same information system. In contrast, agricultural data are collected using different administrative units and are harder to integrate with underweight prevalence figures. Official statistics for livestock numbers in particular fluctuate greatly from one year to the next, raising doubts about data quality. In contrast to agricultural variables such as yields, rainfall is relatively simple to measure and this may account for its usefulness as an indicator of changes in underweight prevalence.

7. USE OF GROWTH MONITORING DATA FOR VALIDATION

7.1 *Introduction*

This chapter develops a methodology for using secondary data to validate a model derived from primary data. At the same time, it addresses two problems commonly encountered in developing models of social behaviour. The first problem is the way in which the scale of observation influences the form of a given model. Perceived causes of phenomena at household level do not always coincide with those apparent in aggregate data for different social groups or regions. Several studies, for example, have illustrated how the apparent causes of disease clusters change with increasing levels of data aggregation (Waller and Turnbull, 1993; Schneider *et al.*, 1993). Such difficulties may also occur when analysing geographical patterns of under-nutrition.

The second problem concerns the issue of model validation that has been well documented in the past. Dent and Blackie (1979, pp. 100-102) have suggested four types of data that can be used for validating a model: historical data used in model construction; historical data not used in model construction; historical data collected since the model was constructed; and data explicitly collected for model validation. They suggest that the latter two types of data are more appropriate for validation, but admit that data collection solely for model validation is expensive. These problems of validation and scale are addressed here by developing a model of health centre attendance based on detailed, household-level data. Aggregated data for each health centre – collected at a different scale - are then used to validate the model. This exercise therefore integrates primary data with secondary data (and so explores Hypothesis A from Chapter 1).

This approach to model validation is considered here in the light of an analysis of patterns of healthcare uptake in Zimbabwe. A model was developed of participation by young children in a growth monitoring programme in the Buhera District in Manicaland Province. Factors affecting participation in the growth monitoring programme were identified on the basis of a household survey. This household-level model of attendance was then used to estimate the number of children weighed in the district's health centres. Simulation results are then compared to government statistics on the number of children attending each health centre, thereby validating the model using an 'unseen' data set.

The operation of the growth monitoring programme has already been described in Chapter 1. In brief, once a child has been weighed, its weight is recorded in two places. Firstly, the weight is marked on the child health card, so that the child's mother has a record of how its growth is progressing and remedial action can be taken if necessary. Secondly, the number of healthy and underweight children is recorded on a tally sheet as weighing takes place. This tally sheet is passed on to the main administrative health centre for the district. Here, if the district hospital has a computer, the information is computerised using custom-written software and then forwarded to the national information centre in Harare. If the district hospital does not have a computer, the information on the tally sheets is added up manually before being forwarded to Harare. The number of computers in use in district hospitals has grown in recent years, and one consequence of this is that the picture of the number of malnourished children is becoming increasingly detailed.

There are, however, two major difficulties in examining the prevalence of underweight children as recorded through the NHIS. The first problem is that not all children visit health centres and therefore not all participate in the monitoring programme. The children who are weighed visit the health centres for a variety of reasons. Some come to be immunised, some because they are ill, whilst others come for routine check-ups. The second problem is that the system does not record details of the socio-economic background of the children concerned, making assessment of possible causes of nutritional problems more difficult. This lack of information about the child's background can be overcome in one of three ways:

- by carrying out ad hoc community-based surveys which examine the characteristics of smaller samples of children in greater detail (such as the DHS survey);
- by asking the child's parents one or two questions at the health centre which give some insight into the home environment (e.g. the number of cattle owned by the child's household). Whilst such information may be useful, the amount of time available for asking questions at a health centre is limited by constraints on nurses' time, etc.
- by identifying the characteristics of the areas where the children who participate in growth monitoring come from.

This latter approach was adopted in Chapters 5 and 6 to assess patterns of malnutrition at district level. Such an approach is relatively straightforward at this level, because many other secondary data sets, such as census information and food aid statistics, are also collected by district. Although some children cross district boundaries to be

weighed and rural children sometimes visit urban health facilities, the majority of children weighed come from the district itself (see section 4.2.3). Growth monitoring data can therefore be linked to other, related data sets quite easily. In the case of individual health centres, however, these problems become much more significant for the following reasons:

- Firstly, there are no clear geographical boundaries associated with individual health centres as there are with districts.
- Secondly, well-equipped health facilities such as hospitals attract patients (including children for growth monitoring) from more distant villages than the more poorly equipped clinics.
- Thirdly, the distances involved in moving between health centres are generally much less than the distances involved in moving between districts, giving people more leeway to choose between clinics.

These problems mean that before patterns of malnutrition at health centre level can be related to causal variables, a model of health facility catchments must be developed.

7.1.1 methods of catchment assessment

There are three main methods available for estimating the catchment areas of facilities. The simplest of these methods is the Voronoi tessellation technique (Thiessen polygons), in which each point is assigned to the catchment of the nearest centre. This has the advantage of being relatively easy to implement, but has several flaws. No distinction is made between the different types of health facility, yet this is clearly important. The catchment areas produced also have sharp, chloropleth boundaries, yet in reality households from the same village may visit different health centres, suggesting that catchment boundaries are indistinct. This phenomenon can be seen in survey results from Murehwa district during 1993, where 15% of households were found to ignore their nearest health centre and use a more distant facility (Bijlmakers *et al.*, 1996: p. 51). Furthermore, the shape of the catchment areas is determined solely by distance and the characteristics of the client households (for example, the extent to which they have access to transport) are not considered.

A slightly more sophisticated approach is to use a gravity model. Gravity models assume that the probability of a client household attending a particular health centre is based on a combination of the attractiveness of the health centre and distance. Typically, the relationship is expressed mathematically in the following way:

$$P_a / P_b = (W_a / W_b) (D_b / D_a)^2$$

{where P_a = the proportion of households at a certain point visiting health centre a ;

P_b = the proportion of households at a certain point visiting health centre b ;

W_a = a weight representing the level of facilities offered by the health centre a ;

W_b = a weight representing the level of facilities offered by the health centre b ;

D_a = the distance between health centre a and the given point;

D_b = the distance between health centre b and the given point (Huff, 1963: p.82). }

Gravity models give a more realistic representation of catchments, in that they recognise that different facilities provide different services and catchment boundaries are indistinct rather than sharp. However, two problems still remain - the models take no account of the characteristics of the individual, and in addition, the weights for the model may be difficult to calibrate.

To overcome these difficulties, an approach similar to that outlined by Birkin *et al.* (1996) was adopted. This entails developing an attendance model statistically from information about visits made by specific individuals to specific health facilities and use this to define clinic catchment areas.

7.2 A model of growth monitoring attendance

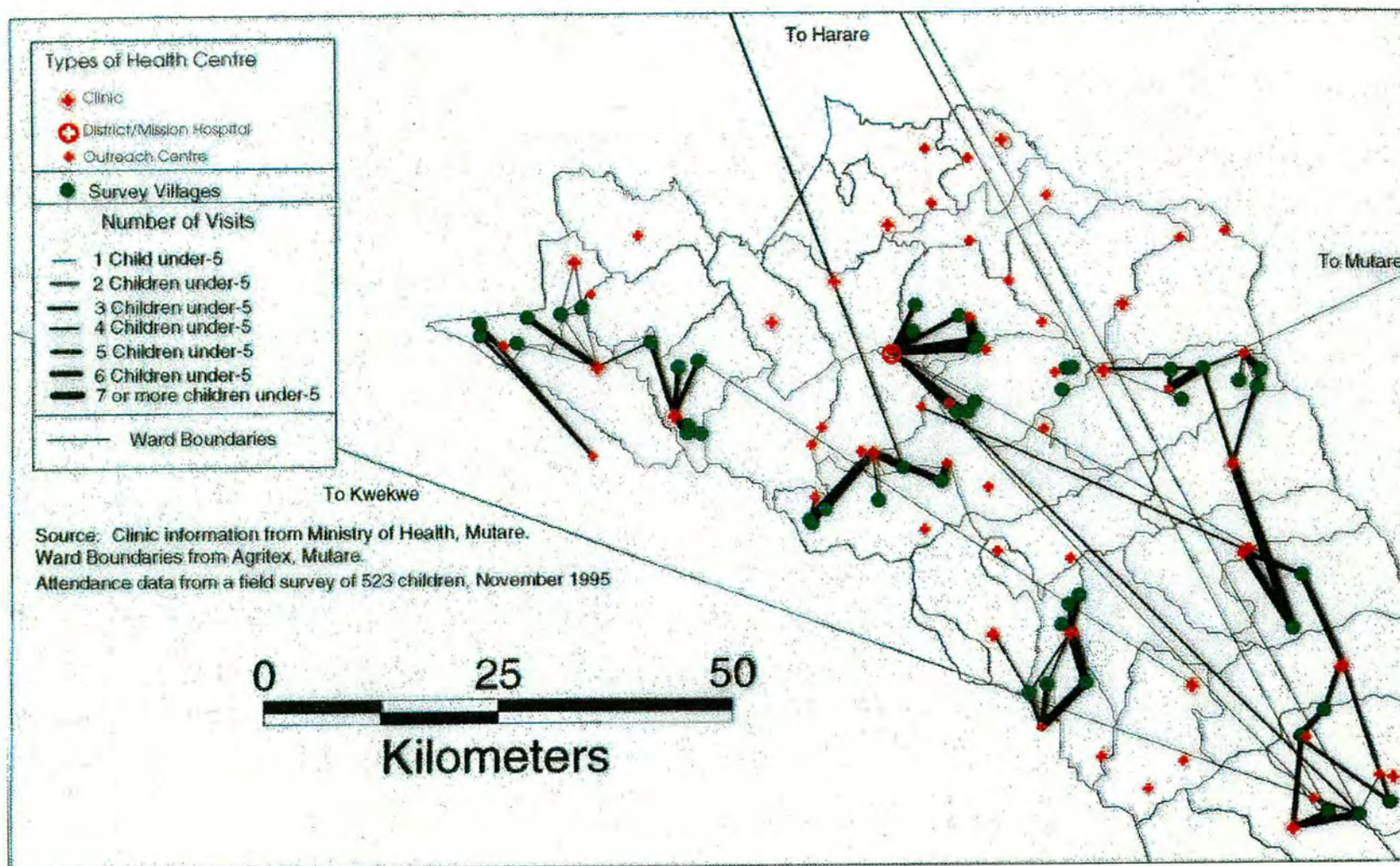
7.2.1 description of data collected

In October 1995, adult carers of 284 pre-school children were asked to identify which health facilities (if any) their children had visited for growth monitoring. The locations of health centres within Buhera had been obtained from the Ministry of Health and Child Welfare, whilst villages participating in the survey were located using a Global Positioning Systems (GPS) receiver. To visualise patterns of attendance initially, a program was written in the MapInfo GIS that plotted lines to illustrate the pattern of attendance. The source code for this program is given in Appendix 2, whilst the pattern of attendance for northern Buhera is illustrated in Map 7.1. It should be noted that parents responding to this questionnaire may not be representative of the population in Buhera as a whole. 4 of the 354 households selected in the sampling framework refused to participate in the survey at any point. Furthermore, by October 1995 when households were asked to answer the

questionnaire used here, a further 61 households had dropped out of the sample, either because of divorce, refusal to participate, death of the household head, or migration out of the district. The 1995 sample thus comprised more stable households at least one year old and under-represented newly formed households such as recent immigrants and newly wed couples. The sampling strategy described in Chapter 2 had also been drawn up to represent rural district residents. Whilst the 1992 census classified all residents of Buhera as “rural”, there are three large settlements (Murambinda, Birchenough Bridge and Dorowa) that contained some 2% of the district’s population at this time¹. The residents of these larger settlements were not represented in the sample.

¹ Of these settlements, census statistics are available for Murambinda only, so I have assumed the other two settlements have equivalent populations in making this estimate.

Map 7.1: Patterns of growth monitoring attendance in northern Buhera district, November 1995



7.2.2 logistic regression analysis

A model of growth monitoring attendance was developed by assessing all the possible visits by the children in the survey to health centres which could have possibly taken place. The probability of attendance at a particular health centre was expressed as a function of:

- the characteristics of the child and the child's family;
- the characteristics of the health centre;
- the distance from the child's home to the health centre;
- and the extent to which other neighbouring health facilities were able to offer similar facilities.

More formally, this relationship was expressed as a logistic regression equation, such that:

$$P = 1/(1 + e^{-Z}) \quad (1)$$

(where P is the probability of a child visiting a health centre and e is the base of natural logarithms. This equation is taken from SPSS, 1993).

In this expression, Z is given by the equation:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_n X_n + \varepsilon \quad (2)$$

(where $X_1 \dots X_n$ represents the characteristics of the health facility, the household, the child, the distance between the two, and competition from other facilities; and ε is a residual error term).

This logistic model was estimated using the method of maximum likelihood.

The characteristics of the child and its household included in the analysis corresponded to those which could be obtained from the 1992 national census statistics, disaggregated by ward in Buhera District. Although this restricted the range of available predictors of formal healthcare participation, the results could be applied to the whole district population by using census data. Household characteristics used in the analysis were therefore:

- the type of water source used;

- the type of sanitation;
- the type of housing (As shown in Chapter 5, type of housing was related to a household asset index and can thus be used as a proxy measure of wealth).

In addition, the type of health centre (rural hospital, central government clinic, or local government clinic) was entered into the regression analysis using dummy variables. For example, for rural hospitals, a dummy variable was created which took a value of one if the health centre under consideration was a rural hospital or zero for any other type of health facility. Effectively, these dummy variables meant that the constant term in equation (2), β_0 , was modified for different types of health centre. The lowest tier of healthcare provision – the network of centres visited by the outreach teams – was not considered in the analysis. This was because of the difficulty of locating all the schools and business centres visited by the outreach teams on the available maps of the district.

Distances between surveyed villages and health centres were calculated in such a way that the effect of roads, rivers, and terrain on movement was explicitly incorporated. As described in Chapter 2, this was achieved through the use of a 'pushbroom' algorithm, which calculates distances from a 'difficulty of movement' map, rather than taking simple Euclidean distance (Eastman, 1989). Slopes were calculated from a Digital Terrain Model of the district and converted to difficulty of movement based on human energy expenditure figures for different types of terrain (James and Schofield, 1990). This was then combined with maps of difficulty of movement along roads and rivers, derived from a series of interviews with local government staff from within the district.

The probability of a household visiting a given health centre is not simply dependent on the level of services, household characteristics, and distance, however. If a facility lies closer to the household that offers identical or better services, then the household is more likely to use this nearer facility. In other words, health centres compete for patients. This effect was represented through a 'competition' variable. Competition was represented by subtracting the distance to the nearest health facility capable of providing the same level of healthcare from the distance to the particular health facility being considered. For example, in Figure 7.1 below, the value of the 'competition' variable for household H and health facility F1 was calculated as the distance from F1 to H, minus the distance from the nearest facility F2 to H. The value of the competition variable is therefore zero for the nearest facility to a given village, and increases for facilities that are further away.

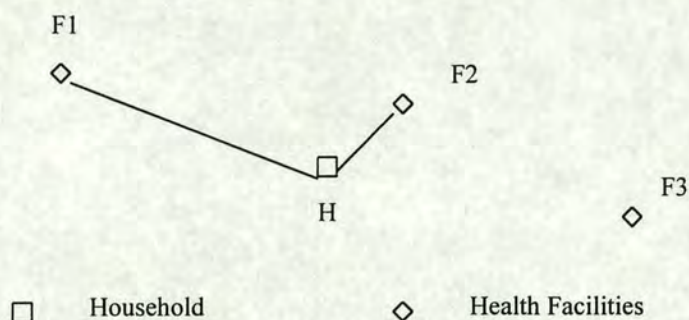


Figure 7.1: Diagram illustrating the calculation of the competition variable.

7.2.3 Results

Table 7.1 shows the results of the logistic regression analysis for hospitals and rural hospitals/clinics. It was found that families in Buhera prefer to use main hospitals for growth monitoring, rather than the more poorly equipped clinics and rural hospitals. In the case of hospitals, growth monitoring participation was related to household water access and distance between the survey village and the hospital. For the smaller rural hospitals and clinics, growth monitoring participation was related to the ‘competition’ variable described above.

Variable	Type of facility	Sign:	Significance
Distance	Hospital	Negative	**
Water Access	Hospital		*
Constant	Hospital	Positive	*
‘Competition’	Clinic	Negative	**
Constant	Clinic	Positive	**

Table 7.1: Results of Logistic Regression Analysis for Hospitals and Clinics (** = significant at the 99% level; * = significant at the 95% level).

The ‘goodness of fit’ of this model can be examined in several ways. For example, the probabilities generated by the model for each observation can be reclassified and compared to the original data set. Model probabilities greater than or equal to 0.5 were considered as ‘true’ predictions, whilst probabilities less than 0.5 were considered ‘false’ predictions. Such results are presented in Table 7.2 for both the hospitals model and the clinics model. For the hospitals model, the model correctly predicted 98.4% of non-attendance and 37.9% of attendance observations, suggesting a good model fit. For the

clinics model, the probability of attendance was so low that all the probabilities generated were less than 0.5 and such cross-tabulation proved an ineffective means of evaluating model performance. Consequently, log likelihood statistics were also used to assess the ‘goodness of fit’ of both models. The likelihood value is a measure of the probability of the observed results occurring, given the parameter estimates (Hair *et al.*, 1995: p. 132). Because this is a small number between zero and one, it is usually expressed as –2 times the log of the likelihood value to give a value analogous to the sum of squared errors in ordinary linear regression. This log likelihood statistic can be used to calculate a ‘pseudo R^2 ’ measure of goodness of fit, based on the formula:

$$R^2_{\text{logit}} = (-2 \log L_{\text{null}} - (-2 \log L_{\text{model}})) / -2 \log L_{\text{null}}$$

{ Where R^2_{logit} is the ‘pseudo R^2 ’ value,
 L_{null} is the likelihood value of a model containing only a constant term and
 L_{model} is the likelihood value of the model being considered (after Hair *et al.*, 1995: p. 132). }

Using this measure, the hospital attendance model had a ‘pseudo R^2 ’ value of 0.33 based on an improvement in –2 log likelihood from 410.1 to 273.2 (N = 576). The clinic attendance model had a lower ‘pseudo R^2 ’ value of 0.11 based on an improvement in –2 log likelihood from 1496.3 to 1333.3 (N = 5184). For both models, a Chi-square test indicated that the improvement in log likelihood was significant at the 99% level.

	Number of children with predicted probability of attending specified hospitals <0.5	Number of children with predicted probability of attending specified hospitals >0.5
Actual number of children not attending specified hospitals	502	8
Actual number of children attending specified hospitals	41	25

(a)

	Number of children with predicted probability of attending specified clinics <0.5	Number of children with predicted probability of attending specified clinics >0.5
Actual number of children not attending specified clinics	5014	0
Actual number of children attending specified clinics	170	0

(b)

Table 7.2: Cross-tabulation of model output against observed patterns of growth monitoring uptake for (a) hospitals and (b) clinics in Buhera district, 1995.

7.2.4 Discussion

The estimated probability of a child attending growth monitoring at a hospital was much higher than for a clinic. There is a clear preference amongst families in Buhera for visiting hospitals for healthcare, but no evidence was found here that households discriminated between the other major tiers of the health system (rural hospitals, clinics, and Rural Health Clinics).

The fact that the ‘competition’ variable was related to growth monitoring participation at clinics but not hospitals is probably because of the lower density of hospitals. The value of the competition variable is always zero when considering the nearest health facility. The two hospitals in Buhera are 106 kilometres apart, whereas the clinics lie much closer together. It therefore cannot be used, for example, to differentiate between a household only a kilometre from the nearest hospital (say, Murambinda) and a household where the nearest hospital is also Murambinda, but which lies 40km away. Consequently, the competition variable was insignificant for hospitals and simple distance proved a better predictor of the number of visits, whereas the competition variable was a better predictor of attendance at clinics.

This method of assessing the likelihood of attendance at growth monitoring has several potential applications:

- It indicates the types of household least likely to participate in growth monitoring, which helps identify bias in the data as it is currently collected and presented.

- It could be used as a tool to site new health facilities (or assess the impact of closure of existing facilities) by targeting groups of households unlikely to attend health facilities under current conditions.
- It provides a means of identifying the areas from which the children who present themselves at health centres are coming from. This at least gives an indication of the environmental and socio-economic background to patterns of malnutrition, often missing in medical statistics for individuals.

However, several weaknesses are apparent in the approach as implemented here. Firstly, the effect of health centres outside Buhera District on patterns of attendance was not incorporated into the competition variable. Although the district is relatively self-contained, being bounded on two sides by the Save and Nyazwidzi rivers, children from the north-western part of Buhera quite often attended growth monitoring in Gutu or Chikomba Districts (see Map 7.1). This problem could be addressed through a more comprehensive survey of existing health facilities. Secondly, restricting the household and individual level predictive variables to those that were collected for the national census is likely to exclude important determinants of healthcare participation. In particular, religious beliefs - which are not covered by the census - affect attendance, with one Christian group with a widespread following in Manicaland Province, the Apostolic Faith, shunning the formal healthcare system.

It should also be noted that the logistic regression model created here estimated the probability of a child *ever* attending growth monitoring, but not the frequency of visits made. This was a constraint imposed by the questionnaire used, which did not ask about frequency of attendance (see the additional question that appeared on the Demographic Questionnaire in Appendix 6 for the exact wording of the question).

7.3 *Simulation of growth monitoring attendance*

7.3.1 Assessment of settlement patterns

This logistic regression methodology enabled the probability of a child attending a given clinic to be estimated. In order to simulate attendance patterns at clinics, a model of the density of the population under 5 years across the district was also required. Clearly, in

calculating overall attendance, the non-agricultural areas of high population density should be given more weight than low population density areas, and places devoid of human habitation should not be included. Inter-ward variation in population density can be found from the 1992 census figures, but no figures exist for intra-ward variation in population density. Kraals in Buhera are seldom found amongst the rocky outcrops found in the north and centre of the district, although some important pre-colonial settlements were located in such areas. In general, flatter areas have been deforested and used as cattle rangeland, whilst 'the hilly areas, rising above the settled plains, (which) have a good tree cover' (Campbell *et al.*, 1989, p. 18). This suggests several variables that might affect the probability of an area being inhabited:

- slope, since this is likely to be much higher on the rocky outcrops devoid of habitation;
- distance to roads, since a common feature of many settlement patterns is to find habitation following the road network;
- and distance to rivers, since Campbell *et al.* (1989) also noted an absence of habitation along the river banks.

Flowerdew and Green (1994) have outlined one method for distributing population data within an enumeration area based on the categories of a second map layer, which is known as the 'EM algorithm'. To investigate whether the methodology could be applied here, it was first necessary to test whether any of the three factors identified above actually influenced settlement patterns.

The 1:50,000 map series of Buhera produced during the 1960s include details of 1,500 minor villages and buildings as well as the major centres of population. This data set provides an indication of intra-ward level variation in population density. In addition, this map series also includes details of the road and track network at that time. Village locations can be analysed in relation to other map layers to produce a model of population density, assuming that the factors which influence the settlement pattern in the district have not changed substantially over the past 20 years even if the spatial distribution of those factors has. However, between 1982 and 1992, population density increased from 31.4 to 38.0 persons per square kilometre (Government of Zimbabwe, 1989b; 1993b). This has intensified both agriculture and the settlement pattern and contributed to the accelerated soil erosion and loss of woodland within the district (Campbell *et al.*, 1989). In addition, the settlement pattern has also been influenced by changes in water availability. In southern Buhera, the proposed irrigation scheme in the Devure area has led to some farmers from outside the district settling near by. Places on the irrigation scheme are restricted to Buhera

residents, so outsiders have moved into Buhera well ahead of the opening of the scheme in the hope qualifying for irrigated land². Nevertheless, it was felt that these sources of error were insufficient to invalidate the method.

As described in Chapter 2, settlement locations were digitised from these 1:50,000 scale maps using a GIS and then converted to raster grids covering Buhera with a resolution of 250 by 250 metres. Contours, spot heights, and the road network were also digitised using a GIS from 1:250,000 scale maps dating from the same period. These map layers were also converted to raster grids with 250 by 250 metre resolution. An interpolation algorithm was then run on the grid containing spot heights and contours to produce a continuous elevation surface, or Digital Terrain Model (DTM). Slopes were then calculated from this DTM using the GIS. All of these map layers were combined with a 1:1,000,000 scale map of drainage derived from the Digital Chart of the World (World Resources Institute, 1995). This map was converted from a simple latitude-longitude reference system to Universal Transverse Mercator grid co-ordinates and rasterised, so that it could be overlaid on the other map layers. Simple Euclidean distances to both roads and rivers were then calculated within the GIS. Major settlements which were either named on the base maps or contained schools were given a code of two; more minor settlements identified but not named on the map were given a code of one. Areas without any recorded settlement patterns were assigned codes of zero.

Anselin and Rey (1991) have noted that the values of a variable at a point on a map are often related to those for surrounding points, a phenomenon known as spatial autocorrelation. This violates one of the assumptions of regression analysis – namely that observations are independent – if such data are analysed statistically. Such auto-correlation may, for example, affect the error term in the regression equation (Anselin and Rey, 1991: p. 2).

One way of measuring autocorrelation prior to performing a regression is to calculate Moran's I statistic, which is given by:

$$I = [n / 2A](\sum_{i,j} \delta_{ij} Z_i Z_j / \sum_{i=1, \dots, n} Z_i^2)$$

² This observation is based on a field visit to Devure and conversations with the agricultural extension worker for Ward 30.

7. Growth monitoring data for validation

(where n = the number of grid cells under consideration;

A = the number of joins between grid cells in the system $\sum_{(2)} \delta_{ij}$;

δ_{ij} = the degree of connectivity between cell i and cell j [1 if they are neighbours, otherwise 0];

and z_i = the value of the grid at i)

(Adapted from Haining, 1990: p. 230).

The calculation of this statistic is illustrated diagrammatically in Figure 7.2, where J is the cell under consideration. For every cell in a raster grid, the value of the statistic is computed based on the value of J and either four surrounding cells (marked as $R_{1..4}$ in Figure 7.2) or eight surrounding cells ($R_{1..4}$ and $K_{1..4}$ in Figure 7.2). By analogy with a chess board, the former method is known as the rook's case and the latter as the king's case. In the King's case, the cells $K_{1..4}$ are given a weight of 0.707 instead of 1 for the parameter δ_{ij} in the equation above. The calculation is repeated for all the remaining cells in the image. Moran's I statistic takes a value of zero for completely random spatial patterns, is greater than zero for clustered geographical distributions, and is less than zero for regular spatial patterns.

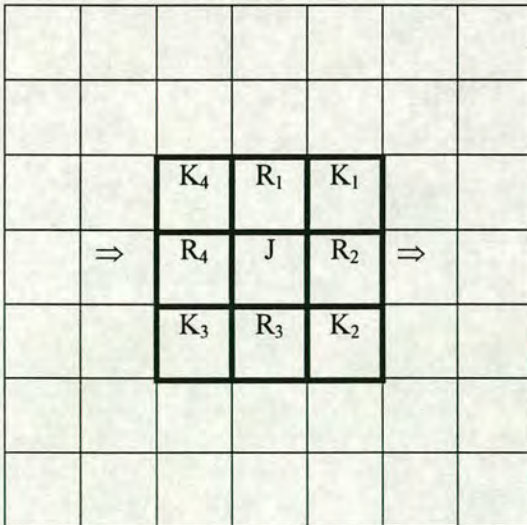


Figure 7.2: illustration of the calculation of Moran's I statistic for a raster grid.

As well as being used to measure autocorrelation, Haining (1990; p. 228-230) and the Idrisi Project (1997) also describe a methodology for eliminating autocorrelation that makes use of the statistic. In this methodology, the value of Moran's I statistic is calculated for an initial grid of known resolution. If autocorrelation is found to exist, every second pixel is sampled from this grid and used to create a new grid, as shown in Figure 7.3.

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Moran's I is recalculated for this new grid, and if autocorrelation still exists, every third cell is sampled from the original grid. The procedure continues until spatial autocorrelation is not longer detected and the data can be used in a regression analysis.

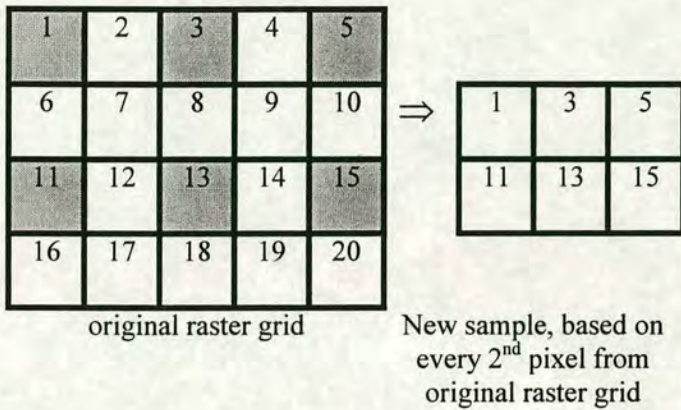


Figure 7.3: Illustration of procedure for elimination of spatial auto-correlation (numbers are labels for each grid cell; shaded cells are selected for inclusion in the new raster grid. This process would be repeated, selecting every 3rd pixel, 4th pixel and so on, until auto-correlation was eliminated.).

This procedure was applied here to the raster grid depicting settlement patterns, which had a resolution of 250 by 250 metres for each pixel. The statistic was calculated using a rook's case (by analogy with a chessboard), in which only the relationship between the pixel under consideration and the 4 cells immediately above, below, and to either side is considered. This was because an initial comparison between the result of the rook's case and king's case calculations showed only a very slight difference between the two. Significant levels of autocorrelation were found to exist in the original grid, with some clustering being evident (see Table 7.3). Consequently, every second pixel across the grid was sampled and the statistic recalculated. Significant levels of autocorrelation still existed according to Moran's I statistic, so every third pixel was sampled and the statistic calculated again. This time, no significant autocorrelation was identified, suggesting that the data from this resolution of sampling would be appropriate for regression analysis. Autocorrelation statistics derived from this procedure are summarised in Table 7.3.

Consequently, every third pixel was sampled across the study area (i.e. a sampling density of 750 metres) and values for slope, distance to roads, distance to major rivers, and the presence of settlement were extracted to a spreadsheet. A logistic regression model was fitted, in which the probability of a grid cell being settled was estimated from distance to roads, distance to rivers, and slopes. For the purposes of this regression model, no distinction was made between major and minor settlements. The results are shown in Table

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7.4 below. It was found that none of these terms influenced the pattern of settlement.

Although this suggests that the distribution of roads, rivers, and slopes did not influence settlement pattern contrary to the remarks of Campbell *et al.* (1989) noted earlier, this may be a result of the coarse scale of the source maps used for these independent variables. If contours and rivers were digitised from the finer scale 1:50,000 maps, this might have resulted in such relationships becoming significant.

Sampling framework	No. of pixels	Moran's I statistic	Z-Statistic
All pixels (every 250 metres)	21492	0.033	6.88 (**)
Every 2 nd pixel (every 500 metres)	5380	0.024	2.48 (*)
Every 3 rd pixel (every 750 metres)	2123	0.007	0.51

Table 7.3: Levels of Spatial Autocorrelation in Settlement Patterns for Different Sampling Resolutions (** indicates autocorrelation significant at the 99% level; * indicates autocorrelation significant at the 95% level).

Variable	Estimated Value of Co-efficient	Significance	R
Distance to rivers	-0.000043	-	0
Distance to roads	-0.000024	-	0
Slope	-.0560	-	0
Constant	-2.0926	**	n/a

Table 7.4: Results of logistic regression analysis of distance to rivers, distance to roads, and slopes on the presence of settlements (** indicates significance at the 99% level; - indicates not significant)

7.3.2 Creation of Population Density Map

An alternative algorithm had to be designed for the creation of a population density map, since settlement patterns could not be related to slopes, distance to roads, or distance to rivers. As described in Chapter 2, the co-ordinates of 185 business centres within the district were obtained from the District Administrator's office. This data set distinguished between three different types of business centre. Murambinda and Birchenough Bridge were identified as Growth Points, following the government's rural development scheme (Wekwete, 1991). Other major settlements were classified as 'rural service centres', and a final category of 'business centre' included other settlements which provided some form of services. These were then mapped out using GIS. On the basis of field visits to Buhera, it was decided that each of the business centres would have a population under 5 years of

approximately 25 individuals, whereas rural service centres comprised approximately 100 individuals under 5 years. From the 1992 census, in which 205 children under 5 years were recorded as residing in the Murambinda Growth Point ward, it was assumed that Birchenough Bridge growth point would also contain approximately 200 children under-5. 25, 100 or 200 children under-5 out of the total recorded for each ward in the census were therefore allocated to each settlement location according to its type. The remaining children under 5 years were then assumed to be evenly distributed across the remainder of the ward.

7.3.3 Simulation of Growth Monitoring Visits

In order to validate the attendance model described earlier, this population distribution map was used as the basis for a simulation that estimated attendance at health centres throughout Buhera. The model described in Section 7.2 was first applied to every child in the district. The probability of attendance for each individual was calculated based on type of water source and distance for hospitals, and on the competition variable for clinics. Raster map algebra modules were used to calculate the probability of attendance based on equations (1) and (2). This was achieved by writing short macros for the Idrisi GIS, the source code for which is included in Appendix 2. Map 7.2 illustrates the output from these macros and shows how the probability of attendance at Chirozva clinic varies across the district. To visualise the output of the attendance model further, the health centre with the greatest probability of attendance for any given point on the map was also identified by means of an Idrisi macro. The results of these calculations are shown in Map 7.3, which shows the health centres most likely to be visited for each grid square in Buhera.

The mean number of children attending each health facility was then calculated by multiplying these probabilities by the number of children at each point in the district. The results of this process were then summed across the district for each health centre.

The questionnaire survey had asked whether or not children under 5 years old had attended health centres, without considering the frequency of visits or the period of time during which the visits took place. Consequently, two adjustments were made so that monthly attendance at health centres could be estimated using the method described above. The questionnaire asked about attendance during a child's lifetime, rather than over a specified period. To compensate for this, the estimated number of visits from the simulation was divided by the average age in months of children in the under-5 age cohort (29 months)

to convert to a monthly figure. In addition, the questionnaire considered which health centre a given child had attended, but not the frequency of visits to that health centre. Government of Zimbabwe (1988) note from an extensive national survey of growth monitoring attendance that children on average make four visits in their first year of life, two in their second, and one in their third. The mean number of visits declined further in the fourth and fifth years, as fewer visits to health centres were needed for immunisation. To incorporate the frequency of visits, the number of simulated visits was then multiplied by the mean frequency of visits by children under 5 (6.4 visits). This gave an estimated mean monthly attendance figure that could be directly compared to the data from the NHIS.

To validate these results, the number of children attending growth monitoring at each health centre per month, averaged over the period January 1990 to September 1995 was then calculated from the NHIS data. Simulation output was then regressed on these actual attendance figures. Following the approach adopted by Kleijnen and Van Groenendaal (1992), an intercept term significantly different from zero was taken as evidence for rejecting the model. Similarly, a slope coefficient significantly different from one would also be taken as evidence for rejecting the model. These two assumptions can be tested simultaneously through the use of an F-statistic (Harrison, 1996), as given by the formula:

$$\frac{(n - 2)\{nb_1^2 + 2nb_1(b_2 - 1) + \sum x_t^2(b_2 - 1)^2\}}{2ns^2}$$

where n is the sample size, s^2 is the residual variance, b_1 is the regression intercept coefficient, b_2 is the regression slope coefficient, and x_t is the t th observation of the real system output.

7.4 Results and Discussion

Table 7.5 shows the results of regressing the real-world data on the simulated numbers of visits. The household-level model failed the simultaneous F-test of goodness of fit test, both when all health centres were included and when health centres likely to be visited by children from outside the district were excluded. The regression, which was based on 21 health centres, had an adjusted R^2 of 0.528. When T-tests were applied to the results

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in Table 7.5, the constant term was found to be significantly different at the 99% level from zero and the slope co-efficient was found to be significantly different from one at the 99% level (although it was significantly different from zero).

Term	Coefficients	Significance
Intercept	112.7056	99.5%
Slope	0.332552	99.5%

Table 7.5: Results of regressing real world data on model output ('Significance' indicates probability that the coefficient value is significantly different from zero).

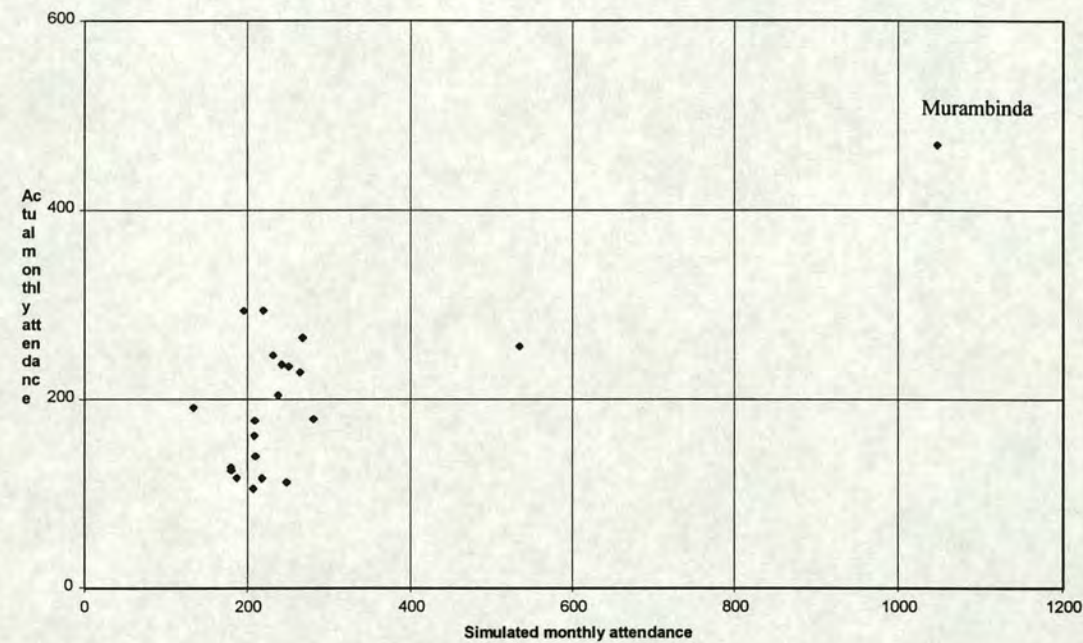


Figure 7.4: Scatterplot of actual mean number of children under 5 attending growth monitoring per month for 21 health centres and the simulated number attending.

Figure 7.4 shows the relationship between actual monthly clinic visits and the clinic visits simulated by the model. Although the simulation model successfully predicts a major difference between the number of attendees at the principal district hospital, Murambinda, and the other health centres, it fails to discriminate differences between attendance at clinics.

Several sources of variation that reduce the goodness of fit between the model output and actual attendance figures can be identified:

- Variation associated with the estimation of attendance behaviour from the household survey data;

- Variation associated with the creation of the population density map for the district;
- Variation associated with the rescaling of the simulation results to take account of the frequency of visits by children;
- The confounding influence of visits by children from outside the district, although this is reduced for much of the area by the natural barriers of the Save and Nyazvidzi rivers;
- Problems of out-of-date census data. The census data on type of water source used in the simulation model relate to 1992, whereas the rest of the model is based on data for 1995. Given that the Non-Governmental Organisation Christian Care was sinking new boreholes in southern Buhera at the time of the household survey, it is highly likely that the pattern of water source use has changed since the census.
- Transcription, data entry, clerical, and other errors associated with the collation of the NHIS actual attendance figures.

Given these five different sources of variation, the fact that the simulation exercise failed the simultaneous F-test is unsurprising. In particular, Pelletier and Johnson (1994) have shown that estimates of under-nutrition prevalence at clinics in Malawi were uncorrelated with estimates from an independent, community-based survey. Whilst this finding does not directly concern attendance, it does raise doubts about the quality of health statistics at clinic level. However, the fact that the simulation model tended to over-estimate attendance suggests that the rescaling adjustment to account for the frequency of health centre use is one of the major sources of error in the model. A revised questionnaire design, asking about frequency of attendance over a specified period, would resolve this difficulty.

Several authors have argued that the simultaneous F-test is too rigorous for agricultural and socio-economic model development. Some have questioned its use with large validation data sets (Thornton and Hansen, 1996), whilst Harrison (1990: p. 183) has suggested that instead: ‘descriptive statistics and subjective tests be used to build up confidence in a model as it proceeds through a number of prototypes’. However, even if the simultaneous F-test is too rigorous, the scatterplot in Figure 7.4 shows that the model was only able to distinguish the higher attendance at Murambinda hospital from all other health facilities. The successful prediction of much higher attendance at this one facility explained the high R^2 and significant, positive slope coefficient of the regression model shown in Table 7.5.

7.5 Conclusions

This chapter developed a model of growth monitoring attendance to explore how secondary data can be used to validate relationships derived from primary data. It thus examined one possible method for relating data that had been collected at different scales – information about health facilities on the one hand and information about households on the other.

The simulation model presented here failed a regression-based validation test, but was able to distinguish between poorly attended clinics and well-attended hospitals. The attractiveness of hospitals to patients is thus borne out both by the household survey and by health statistics collected by government. The failure of the attendance model to distinguish much more than this is probably due to the compound effect of several different sources of error. These errors are related to the household-level attendance model, to the population density model, to the effect of attendees from outside the district, and to the data quality of the validation health centre statistics. It may be that through revising the questionnaire design to account for differing frequencies of attendance, the model's performance could be improved. The model might also prove more robust if applied in a developed country with better resources for health information systems, instead of a rural part of Africa.

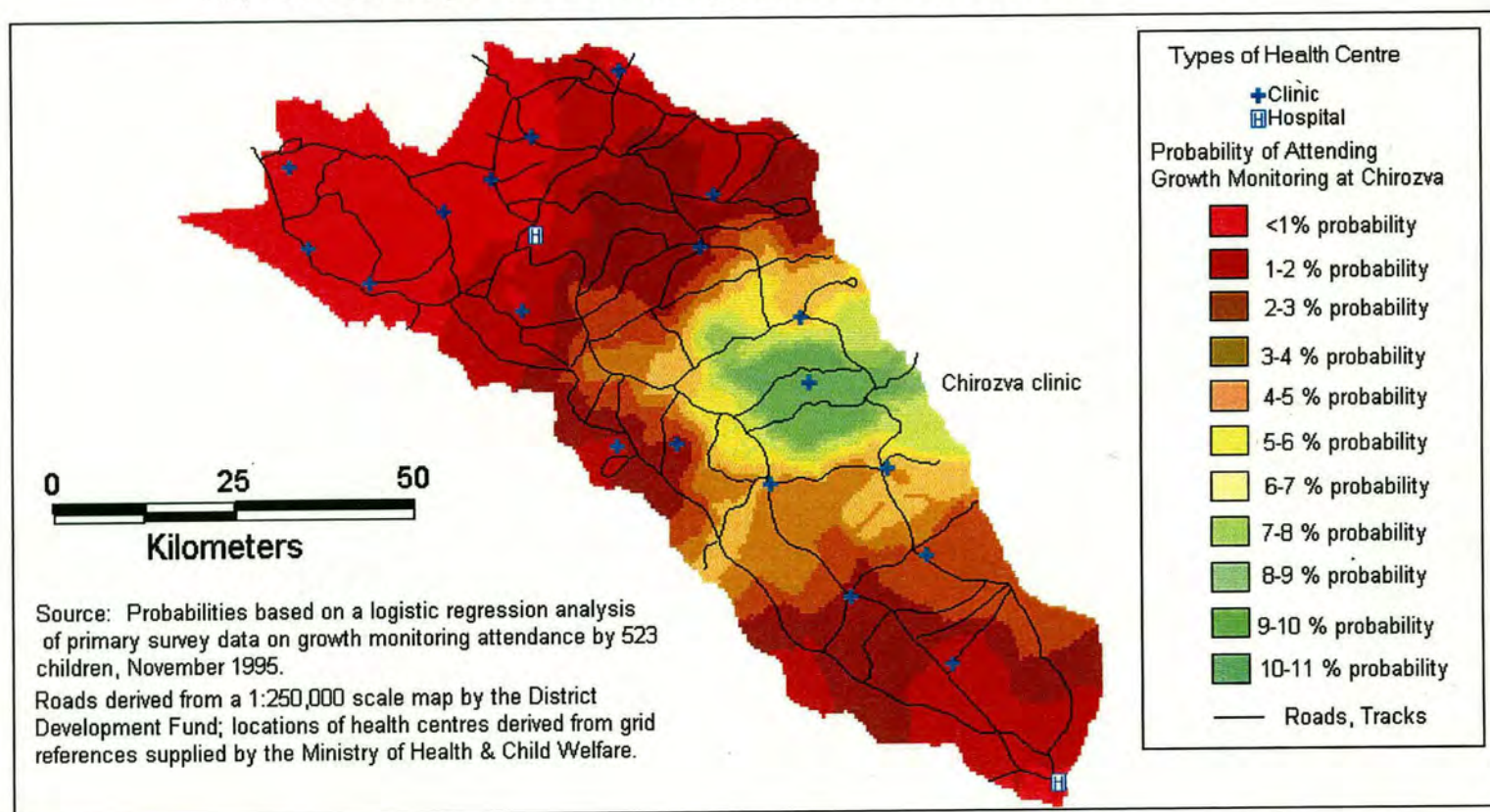
If the accuracy of this model could be improved, it would have numerous potential applications. The attendance model developed here could be coupled with a household-level model of the causes of under-nutrition. In the same way as the total number of attendees at each health centres was calculated here, so separate totals could be kept for the number of healthy and underweight children attending health centres, as predicted by such a model. This output from the household-level model of under-nutrition could then be validated against clinic-level data for the same period, thereby improving confidence that the household-level causes of under-nutrition had been identified correctly.

Similarly, the different maps depicting the probability of attendance at each health centre (as illustrated by Map 7.2) could also be used to estimate the characteristics of health facility catchments. For example, the probability map for a given clinic could be combined with a map of the percentage of households without access to a protected water source and the mean percentage of households without protected water in the clinic catchment calculated. This process could be repeated for all health centres and underweight prevalence

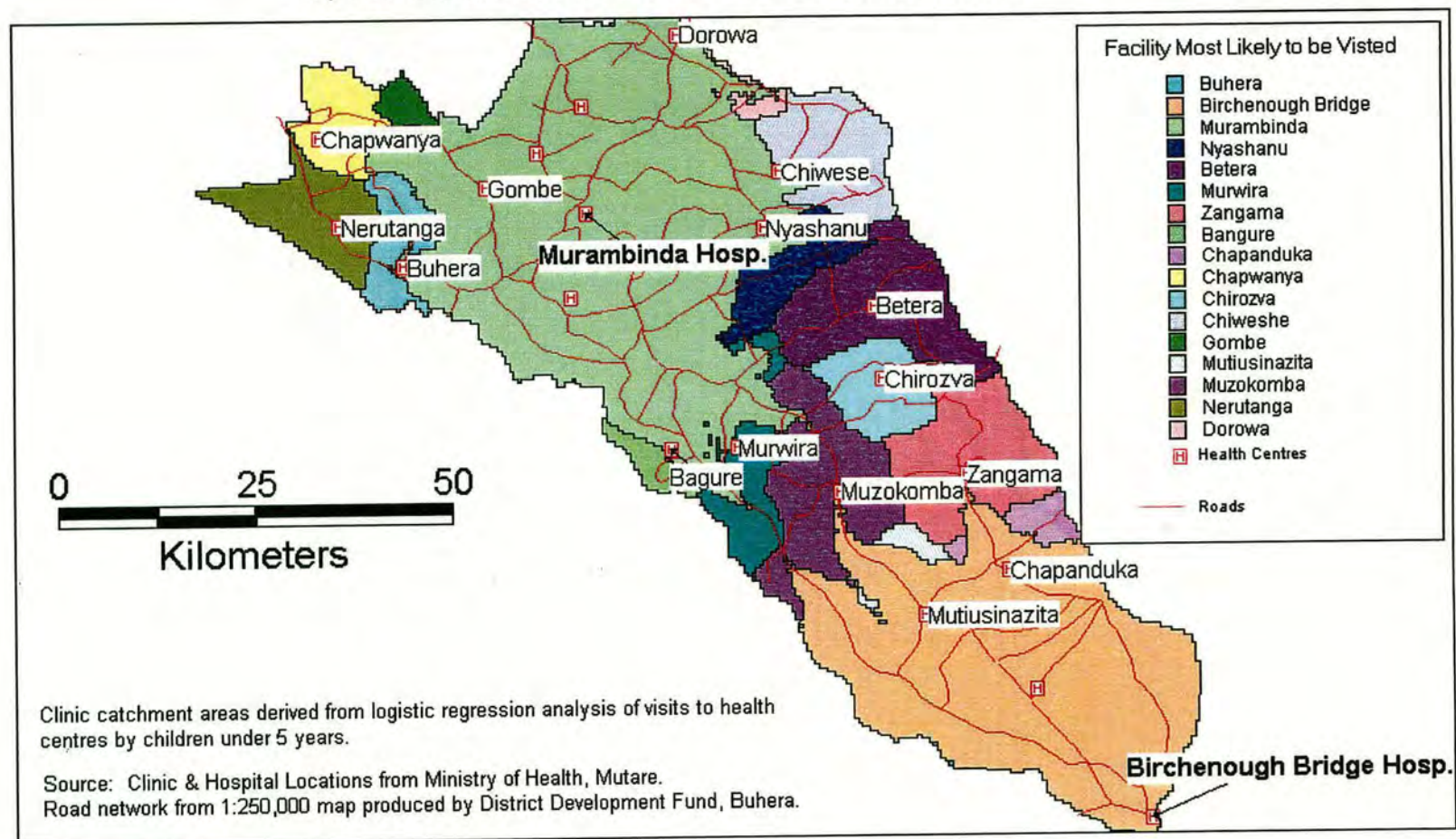
related to catchment characteristics in a manner similar to the district-level analysis undertaken in Chapter 5. This would thus enable clinic-level health centre statistics concerning nutritional status to be related to the socio-economic and environmental conditions of clinic catchments.

In addition, the same technique applied here may have potential in planning healthcare delivery. For example, it could be used to identify areas where the probability of healthcare uptake is low so that suitable locations could be identified for potential new facilities. Alternatively, households who seldom make preventative visits to health facilities (such as visits for growth monitoring) could be specifically targeted through a health education campaign. However, all of these potential applications would require better attendance model performance than was identified here.

Map 7.2: Probability of Growth Monitoring Attendance at Chirozva Clinic



Map 7.3: Catchment Areas of Health Centres in Buhera District



8. Conclusions

As with the introduction to this study, the conclusions to the thesis can be drawn together under the three themes introduced at the outset of this work. The first set of conclusions relate to the general issue of secondary data analysis, whilst the second set relate to the operation of the government's information system, and the third set to child under-nutrition in Zimbabwe. Table 8.1 shows how these conclusions relate to the hypotheses described in Section 1.4. In addition, many directions for further research can be identified.

8.1 *Conclusions about secondary data analysis*

Secondary data became increasingly easy to obtain during the course of the thesis, with more and more data sets becoming available through the US Geological Survey's African Data Dissemination Service and through the DHS series of surveys. This makes a re-evaluation of the role of secondary data timely. These conclusions are related to data collection and quality and also to methods of analysis.

8.1.1 Data collection and quality issues:

- Some areas of secondary data collection in Zimbabwe require greater support and investment.

Although many of the data sets collated were well documented and usable, several proved almost unusable in their current form. The consumer food price data set was difficult to use because markets where prices were collected could not be located. The usefulness of the local government inventory of water sources was limited by erroneous grid references and the inclusion of boreholes and wells that had dried up or were broken. The archive of livestock numbers was difficult to use because of inconsistent reporting units over time. Similarly, an up-to-date road map for the whole country proved difficult to obtain. Each of these databases would benefit from investment to strengthen data collection, processing, and management. At the time of writing, projects had been set up to improve water source inventories in Zimbabwe and to survey the locations of dip-tanks across the country using GPS for better livestock monitoring. However, there is still scope for additional projects to

update the country's road map and to support the price monitoring programme run by Agritex.

8.1.2 Conclusions about methodology for secondary data analysis

- Secondary data can be used to validate models calibrated from primary data.

A model of healthcare uptake was validated by comparison with attendance statistics collected at health facilities. This is a rigorous test of a household model both because the validation data are collected at a different scale and because they are collected by a different organisation.

- Simultaneous analysis of data across different scales can be undertaken to increase confidence in the conclusions reached.

In the analysis of seasonality in Chapter 4, aggregate national statistics showed the same seasonal variability in percentage under-nutrition as many of the districts in the country. Similarly, in Chapter 6 both national health statistics and figures for many individual districts showed a correlation between reported cases of diarrhoea and under-nutrition rates. The fact that results were similar at the two scales of analysis strengthened belief in the conclusions reached.

Overall, integration of data collected by the different organisations proved difficult and time-consuming, despite the fact that so much information was available. This was partly because the various organisations use different spatial units to collect data, so many data sets had to be aggregated to district level. When secondary health data were integrated with information from other sources, the results were mixed. In Chapter 5, there was a clear relationship between census variables and the long-term average prevalence of underweight children. In Chapter 6, however, no relationship was found between underweight prevalence and several variables that one would expect to strongly influence nutritional status. Negative findings such as this from analyses of secondary data are difficult to interpret. The apparent lack of a relationship could be a consequence of poor data quality or genuinely reflect reality, but it is difficult for the secondary data analyst to decide between these two possibilities.

Hypothesis	Conclusion
A. Analysis of primary and secondary data may reveal alternative apparent causes of poor nutritional status: it is possible to reconcile conflicts between these different sources of data through an integrated analytical approach.	FALSE for this context – a simulation of health centre attendance calibrated at household level could not reproduce the pattern of attendance as recorded at health centre level. However, a methodology was developed to validate a healthcare uptake model based on primary data against secondary data.
B. The National Health Information System's growth monitoring programme provides useful and accurate information concerning the nutritional status of children under 5 years.	PARTLY TRUE – the information is useful for distinguishing seasonal and provincial variation in underweight prevalence, but no conclusions could be reached about its usefulness for inter-annual comparisons.
C. Prediction of nutritional status is possible from secondary data alone, without the need for household or rapid rural appraisal surveys.	TRUE – Forecasts could be made based on rainfall and reported cases of diarrhoea. However, in both cases the accuracy and usefulness of the predictions is limited.
D. The combined effects of the Economic and Structural Adjustment Programme, the HIV/AIDS epidemic, and drought have increased the proportion of children suffering from poor nutritional status since 1991.	FALSE according to this data set – though changes in attendance patterns may have influenced this conclusion.
E. The peak season for nutritional problems in Zimbabwean children is immediately pre-harvest in January-March, when food security is low and diarrhoea and malaria rates are high.	TRUE – this was the case both at national level, and for many of the district-level statistics.
F. High prevalence of underweight children is related to health factors as well as food security.	TRUE – a relationship was found between monthly fluctuations in underweight prevalence and reported cases of diarrhoea. A relationship was also found between long-term average underweight prevalence and health environment characteristics such as sanitation.

Table 8.1: Evaluation of research hypotheses

8.2 *Conclusions about the information system*

8.2.1 Evaluation of the current growth monitoring scheme

Several conclusions can be drawn about the usefulness of data collected through the existing growth monitoring scheme:

- The main problem behind the NHIS growth monitoring scheme is that children are weighed at clinics and therefore are potentially unrepresentative of the general population.

Children who stay away from clinics may be poorer and may be more likely to be underweight than those who attend.

- The weight-for-age statistics gathered by the system were valid for ranking provinces in terms of their nutritional problems.

Provincial estimates of underweight prevalence were not significantly different from those in an independent survey and both sets of estimates were well correlated.

- national estimates of underweight prevalence in children under 2 years can be improved by applying a geographical and age cohort weighting system.

Estimates of national underweight prevalence from the growth monitoring scheme and an independent survey were of a similar magnitude, but significantly different. When the weighting system was applied, there was no significant difference between the two estimates.

- Trends in under-nutrition prevalence derived from growth monitoring data should be treated with caution.

This is because attendance has varied over time and so the sample of children participating in the scheme at different times may not be comparable. Attendance increased up to 1991, but then declined thereafter.

- Growth monitoring statistics can be used for identifying seasonal variation in underweight prevalence.

This is because there was no evidence of significant seasonal variation in participation in the scheme.

- Changes in underweight prevalence can be forecast from secondary data, but the usefulness of these forecasts is limited.

Changes in child under-nutrition could be forecast a year in advance from rainfall data and forecast a month in advance based on reported diarrhoea cases. However, the usefulness of annual predictions is limited by their low accuracy. Similarly, the usefulness of monthly predictions is also limited, since little preventative action can be taken in the space of only one month.

8.2.2 Future options for the growth monitoring scheme

The growth monitoring programme was adequate for distinguishing differences in prevalence across seasons and provinces, but its ability to distinguish trends was questionable. One obvious question that arises from this review of the quality of growth monitoring information is whether or not the scheme should continue in its present form. Possible alternatives might include:

- Abandonment of the growth monitoring scheme, without replacing it with any form of nutritional information system.* Abandonment of the scheme might be justified if the information collected was not used to inform decision making (particularly given that the Zimbabwean government is under increasing pressure to cut public expenditure). However, there is evidence that information from the scheme is used in decision-making (see below).
- Replacement of the growth monitoring scheme with more infrequent, community-based surveys.* For example, the Demographic and Health Surveys discussed in Chapter 3 might be considered as a possible replacement for growth monitoring. However, with its current timing the DHS is too infrequent to replace the growth monitoring scheme as a nutritional surveillance system. The DHS survey takes place every 6 years – the first DHS survey in Zimbabwe took place in 1988 and the second in 1994. It takes a further one to two years for preliminary results to be produced following the initial survey (Macro International, 1990 & 1995). Considerable changes could occur in the seven to eight years that could potentially elapse before survey results were available.
- A change in the group surveyed, for instance by measuring children at school or pregnant mothers at health centres.* Clearly, such a modification to the scheme would

still be prone to problems of sampling bias, since a proportion of the general population would be likely not to attend school or not to give birth at health centres. However, the change might be justified if there was evidence that another population cohort apart from children under 5 years were the most nutritionally vulnerable.

- D. *Replacement of the scheme with regular community-based measurements, based at specific locations considered representative of the general population.* This alternative would certainly overcome the problem of sampling bias, but the cost would be likely to be much higher than that of the growth monitoring scheme.

Although each of these options has some merit, there are some compelling reasons for retaining the existing growth monitoring scheme:

- Information from the scheme is actually used to support decision-making.

Clearly, any information system is only useful if the information gathered aids decision-making in some way and this does appear to be the case in Zimbabwe. In terms of geographical targeting of nutritional problems and identification of trends *within government*, it is clearly difficult for an outsider to speculate about how information from the system is actually used without undertaking a participatory study such as that of Pelletier and Msukwa (1991). However, *outside government*, there is evidence of NGO's making use of growth monitoring data to assess the impact of structural adjustment on welfare. For example, Watkins (1995: pp 83-85) note that ESAP has led to an increase in both infant and maternal mortality, but that child nutritional status has continued to decline if anything. Similarly, Muir (1993) cites growth monitoring data revealing the highest prevalence of underweight children in Binga district. This information may have been influential in Save the Children Fund selecting the area for particular assistance.

- The skills and infra-structure for the administration of the NHIS growth monitoring scheme are already in place.

The adoption of a new system, or revision of the existing system, would require investment in computer systems and retraining. Such changes are likely to disrupt the flow of information for some months, as occurred when the NHIS T5 form was revised in 1993.

- The abandoning of the growth monitoring scheme would mean the end of a long time series of monthly nutritional data.

Although there are concerns about changing levels of participation in the scheme, it has at least consistently used the same reference population and standard, and weighed the same age cohorts of children through time. It should be noted that trends are difficult to infer even from the summary reports of the two DHS surveys. This is because the first DHS survey measured weight and height in children under 5 years, whilst the second DHS survey measured weight and height in children under 3 years. Aggregate prevalence figures for the two groups, as presented in the summary reports, are thus not directly comparable. Trends can only be estimated by returning to the raw data and recalculating figures for 1988 based on children under 3 years.

- The growth monitoring scheme may have benefits not only at the population level, but also at the individual level.

When UNICEF adopted growth monitoring as part of their strategy to improve child health, most of the reasons cited for implementing growth monitoring concerned the individual. These benefits included maternal education, identification of children at risk of nutritional problems, and proper timing of supplementary feeding. However, the benefits derived from the growth monitoring chart have recently been called into question in a study of growth monitoring in India (George *et al.*, 1993). This suggests that these individual level benefits should also be evaluated in Zimbabwe before any decision is reached about the future of the scheme.

Given these issues, it would be unwise to abandon the growth monitoring scheme without a full consideration of its organisational context, cost, and the potential benefits accruing to the individual child or mother. The current system, whereby the growth monitoring data can periodically be validated by an independent, community-based DHS survey, does seem to provide a compromise between timeliness, accuracy, and cost. The publication of raw DHS data is important in ensuring that results from the two sources can actually be compared, so this procedure should be encouraged. As such, there may be merits in maintaining the system in its current form, particularly given the additional funding necessary to change the system. Furthermore, given the poor performance of growth monitoring schemes elsewhere in southern African (Pelletier and Johnson, 1994), staff at the Ministry of Health and Child Welfare should be credited with running an effective scheme in Zimbabwe. Thus, the evidence presented here suggests that the existing scheme coupled with the DHS survey should remain in place, rather than any of the possible alternatives (A – D) discussed above.

8.3 Conclusions about underweight prevalence and nutrition

Several conclusions can be drawn out from this thesis about nutritional status amongst children under 5 years:

- The January-March period was the peak season for underweight prevalence, according to the growth monitoring data.

This is the period when food is in short supply prior to harvest, and when diseases such as diarrhoea and to a lesser extent malaria will also affect nutritional status. This phenomenon is not an artefact of variable attendance at growth monitoring, since this was found not to vary by season. This finding confirmed Hypothesis E.

- There is no evidence of an increase in under-nutrition prevalence between 1988 and 1995 in the growth monitoring data.

This was surprising, given that Zimbabwean children have been particularly affected by drought, the HIV/AIDS epidemic, and by structural adjustment in the latter half of this period. This finding apparently refuted Hypothesis D.

- the apparent improvement in nutritional status could be due to a decline in participation in growth monitoring.

As noted earlier, this trend of improvement may not be representative of the Zimbabwean population as a whole, since there is some evidence that some children are staying away from growth monitoring, perhaps because of the introduction of health fees or because of a decline in service provision. These children that have stopped attending growth monitoring may be poorer and therefore more likely to be undernourished than those who attend, thus creating bias in the data.

- urban areas such as Harare and Bulawayo had very low prevalence of underweight children, whilst rural areas, particularly in Matabeleland, had much higher prevalence.

This confirms the geographical pattern of child under-nutrition described elsewhere (Tagwireyi and Greiner, 1994; Madzingira, 1995).

- The long-term average percentage of underweight children was related to poverty.

Areas with unprotected water supply, poor sanitation and housing, and largely rural populations showed higher rates of under-nutrition. This finding suggested that health-related factors also contributed to under-nutrition (supporting Hypothesis F).

- Annual changes in the under-nutrition rate recorded by the NHIS were related to changes in rainfall.

Other possible indicators such as maize yields and demand for drought relief were weakly related to under-nutrition, whilst changes in animal numbers and the number of recorded cases of certain diseases were not related to the under-nutrition rate, though this may have been due to problems of data quality.

- Monthly changes in the prevalence of underweight children were correlated with changes in reported cases of diarrhoea in the previous month

This finding confirms that there is a close relationship between health status and nutritional status. It suggests that adequate food access is not the only precondition for healthy nutritional status, again supporting Hypothesis F.

8.4 Areas for further research

8.4.1 Possible further research outside Zimbabwe

The work presented here could be extended in many different directions. One issue regarding the evaluation of the NHIS growth monitoring scheme is whether the results might hold true for other countries within the region. The conclusions of other studies reported in Chapter 3 suggest that the usefulness of the data collected and the existence of bias depend on the specifics of the monitoring scheme. In Malawi, for example, growth monitoring was found to under-estimate underweight prevalence, whilst in Swaziland, growth monitoring over-estimated prevalence. This implies that it would be dangerous to make any inferences about growth monitoring elsewhere on the basis of the Zimbabwean results. However, the methodology presented in Chapter 3 draws on three sources of data available in many other southern African countries: computerised monthly growth monitoring data; population census data; and the Demographic and Health Surveys. In other words, whilst the

conclusions about the quality of NHIS data in Zimbabwe cannot be generalised to other southern African countries, the *methodology* used to evaluate the system is transferable since it makes use of widely available data sets.

Another possible follow-up study to the work in Chapter 7 would be to attempt the validation of a household-level healthcare uptake model with secondary data in a developed country. With more resources available for data collection and running health information systems in this context, it might be that a better model fit with health centre data could be achieved.

8.4.2 Possible future research within Zimbabwe

Possible areas of future research within Zimbabwe are related to the operation of the nutritional information system. The suggestion that the reduction in the proportion of children attending growth monitoring is due to problems in maintaining outreach services could be further investigated through a follow-up study of mobile health team operations. Although Bassett *et al.* (1997) have already undertaken a qualitative study of the impact of ESAP on healthcare delivery, a more quantitative study could focus specifically on growth monitoring. Such a study could examine fuel and vehicle availability and the extent to which outreach services can be maintained. A supplementary analysis of changes in immunisation rates from the NHIS data set could also provide evidence on the impact of funding cuts and health fees on healthcare delivery.

An evaluation of the use of nutritional data and the organisational context of the National Health Information System would also prove very valuable. However, such a study would probably require participant observation from within government (Pelletier and Msukwa, 1991) and so might be better undertaken by a Zimbabwean researcher.

Another subject for further investigation would be the appropriateness of children under 5 years as the cohort used in growth monitoring. One option would be to take anthropometric measurements of all community members (i.e. adults and schoolchildren as well as children under 5 years). Comparison of under-nutrition prevalence by age cohort would reveal whether those under 5 years are the nutritionally most vulnerable. The 1994 DHS data set could also be used to assess this issue, since it includes weight and height measurements of both mothers and children under 3 years of age. This data set could be

used to investigate how often an undernourished mother also has undernourished children. This information could be used to assess the suggestion that the nutritional status of dependants in the household is affected by the nutritional status of those in the economically active age cohorts. If such a study showed that maternal nutritional status had a major impact on other members of the household, this would justify some type of maternal nutritional monitoring. At the same time, separate models could also be developed for mothers and children of the causes of under-nutrition using the DHS data. An examination of the differences between the two models might also highlight some of the limitations of monitoring young children.

Given that this thesis was based largely on secondary data, another direction for further work would be through primary data gathered from a field survey. P Mucavele from the Zimbabwe project is currently undertaking complementary analysis of many of the issues discussed here (including factors affecting health centre attendance and factors affecting under-nutrition at individual level). An interesting supplementary analysis at this individual level would be to assess the effectiveness of growth monitoring in terms of its educational benefits and for enhancing normal growth in children.

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Appendix 1: Sample T5 Health Statistics Summary Sheet

62775-9
T 5

MINISTRY OF HEALTH
MONTHLY RETURN

Name Buhesa District

From HIS To P.M.D Month and year APR 92

Clinic/Hospital/DMO/PMD

DISTRICT HEALTH OFFICE
BUNERA DISTRICT
14 MAY 1992
Private Bag 625, BUNERA

IMMUNISATIONS		
Vaccine and dose	Under one year	One year and over
Total attendances	2857	3224
BCG initial	550	136
BCG booster (5 years and over)	—	180
Polio 1	471	251
Polio 2	350	130
Polio 3	361	94
Polio booster 1 (18 months)	—	358
Polio booster 2 (5 years and over)	—	175
DPT 1	586	26
DPT 2	433	44
DPT 3	391	65
DPT booster (18 months)	—	269
DT 1	—	226
DT 2	—	142
DT booster (5 years and over)	—	182
Measles	371	178
Primary course completed	286	379

ANTENATAL AND POSTNATAL	
First antenatal visits	587
Repeat antenatal visits	1718
Antenatal referrals	69
Postnatal visits up to 6 weeks	248

MATERNITY	
Total live deliveries	191
Live births under 2.5 kg	9
Referral to hospital	28
Still births under 2.5 kg	—
Still births 2.5 kg and above	2
Neonatal deaths	1
Maternal deaths	—
Birth records issued	250

TETANUS TOXOID		
Women of child bearing age	1st dose	270
	2nd dose	185
	Booster: subsequent pregnancies	71
CASUALTIES		114

MASTER CARD SUMMARY			
Age in months	Total children weighed	Children below the line	%
0-5	1271	4	5.0
6-11	1591	18	7.4
12-23	1882	360	19.1
24-59	1588	361	22.7

Date reported 12/5/92

Reported by: Imanolu

Name HIS

Title HIS

DISTRICT HEALTH OFFICE
BUNERA DISTRICT
14 MAY 1992
Private Bag 625, BUNERA

Appendix 2: Sample Program Code for Idrisi & MapInfo GIS Systems

The more complex GIS operations used in Chapter 7 were written in the form of Idrisi for Windows macros. Further documentation on the syntax for Idrisi macro language can be found in the reference manuals and on-line help documentation. Three of the more complex macros are included here:

- a macro which calculates the probability of attendance at a clinic across the district;
- a macro which calculates the probability of attendance at a hospital across the district;
- a macro which finds the serial number of the health centre most likely to be attended for each pixel in the district;

The Idrisi for Windows macro below was used to derive probability of attendance maps for each of the clinics in Buhera, following the methodology described in Chapter 7. The macro below calculates the probability of a child attending a given clinic, based on the equation $1/(1 + e^{0.0491 * \text{competition variable} + 2.0147})$. A section of the macro is presented here, which calculates the probability for two of the clinics in Buhera district.

[Health is the name of an image in which each health facility in Buhera has been given a unique serial number. In this section of code, the health centre with identifier 21 is reassigned a code of one and all other health centres are assigned a code of zero.]

```
reclass x i health health2 2 0 1 21 0 22 100 -9999
```

[A distance calculation is now undertaken, which calculates distance from all the cells with codes greater than zero – in other words, from health centre 21. The distance calculation uses a ‘difficulty of movement’ map, as described in Chapter 7, called friction.]

```
costpush x health2 friction temp1
```

[The distance to the nearest clinic for each pixel has already been calculated and stored in the image Mindist. The distance to the nearest pixel is subtracted from the distance to health centre 21 to give the value of the competition variable described in Section 7.2.2.]

```
overlay x 2 temp1 mindist temp2
```

[The competition is now multiplied by the co-efficient from the logistic regression equation, -0.0491]

```
scalar x temp2 temp1 3 -0.0491
```

[The constant term from the logistic regression equation is now added to the result]

```
scalar x temp1 temp2 1 -2.0147
```

[The result is now multiplied by -1, following the standard form for a logistic regression given in equation (1) in Chapter 7]

```
scalar x temp2 temp1 3 -1
```

[This value, known as $-z$, is now transformed to give e^{-z}]


```

transfor x temp1 temp2 3
[Again following the standard form for a logistic regression given in equation (1) in Chapter
7, 1 is added to the result]
scalar x temp2 temp1 1 1
[The reciprocal of the result is then calculated using the Idrisi 'transfor' command to give the
final probability of attendance at health facility 21 for each pixel]
transfor x temp1 centre21 1
[The calculation is now repeated for the next clinic, which has a serial number of 22]
reclass x i health health2 2 0 1 22 0 23 100 -9999
costpush x health2 friction temp1
overlay x 2 temp1 mindist temp2
scalar x temp2 temp1 3 -0.0491
scalar x temp1 temp2 1 -2.0147
scalar x temp2 temp1 3 -1
transfor x temp1 temp2 3
scalar x temp2 temp1 1 1
transfor x temp1 centre22 1

```

The following macro calculates the probability of attendance at growth monitoring for a hospital, rather than a clinic. Sample code is again presented here for Birchenough Bridge hospital in the south of Buhera.

```

[Health is the name of an image in which each health facility in Buhera has been given a
unique serial number. In this section of code, the health centre with identifier 2
(Birchenough Bridge hospital) is reassigned a code of one and all other health centres are
assigned a code of zero.]
reclass x i health health2 2 0 1 2 0 3 100 -9999
[The calculation is now undertaken, which calculates distance from all the cells with
codes greater than zero – in other words, from health centre 2. The distance calculation uses
a 'difficulty of movement' map, as described in Chapter 7, called friction.]
costpush x health2 friction temp
[The competition is now multiplied by the co-efficient from the logistic regression equation,
--0.0807]
scalar x temp temp2 3 -0.0807
[The constant term for unprotected water sources from the logistic regression equation is
now added to the result. The logistic regression equation contained two dummy variables,
one for households using protected water sources and one for households using rivers as
their water sources. It can thus be thought of as having three different constant terms – one
for households with unprotected water sources, one for households with protected water
sources, and one for households using rivers or dams]
scalar x temp2 temp 1 0.9148
[The result is now multiplied by -1, following the standard form for a logistic regression
given in equation (1) in Chapter 7]
scalar x temp temp2 3 -1
[This value, usually referred to as -z, is now transformed to give  $e^{-z}$ ]
transfor x temp2 temp 3
[Again following the standard form for a logistic regression given in equation (1) in Chapter
7, 1 is added to the result]
scalar x temp temp2 1 1
[The reciprocal of the result is then calculated using the Idrisi 'transfor' command to give the
final probability of attendance at health facility 21 for each pixel]

```



```

transfor x temp2 prob3unp 1
[The process is repeated, but this time using the constant term for households using protected
water sources]
costpush x health2 friction temp
scalar x temp temp2 3 -0.0807
scalar x temp2 temp 1 1.2325
scalar x temp temp2 3 -1
transfor x temp2 temp 3
scalar x temp temp2 1 1
transfor x temp2 prob3pro 1
costpush x health2 friction temp
[Once again the process is repeated, but this time using the constant term for households
using rivers or dams as their main water source]
scalar x temp temp2 3 -0.0807
scalar x temp2 temp 1 -0.1139
scalar x temp temp2 3 -1
transfor x temp2 temp 3
scalar x temp temp2 1 1
transfor x temp2 prob3riv 1
[Separate probability maps have now been computed for the three different types of
household (i.e. those with protected water sources; those with unprotected water sources; and
those using rivers or dams for water). These are now multiplied by the proportion of
households in each ward using each of type of water source. This information is taken from
the 1992 census and is stored in three images: riverw, protectw, and unprotw.]
overlay x 3 prob3riv riverw temp
overlay x 3 prob3pro protectw temp2
[The results are then summed to give the overall probability for each pixel of a child
attending Birchenough Bridge hospital for growth monitoring.]
overlay x 1 temp temp2 temp3
overlay x 3 prob3unp unprotw temp2
overlay x 1 temp3 temp2 birch

```

The macro below finds the serial number of the health facility most likely to be visited for each pixel across Buhera district.

```

[The probability of attending the health facility with serial number 2 is subtracted from that
for the health facility with serial number 1. These probabilities were created using the
previous two macros and are stored in the images centre1 and centre2.]
overlay x 2 centre1 centre2 temp
[The resultant image is reclassified. Any values less than zero are assigned the serial number
2, whilst values greater than zero are assigned the serial number 1. The output image,
maxid, thus contains the serial number of the health centre most likely to be attended out of
the two.]
reclass x i temp maxid 2 2 -100 0 1 0 100 -9999
[Next, the greater of the two attendance probabilities is calculated for each pixel.]
overlay x 9 centre1 centre2 max
[Next, the probability of attending the health centre with serial number 3 is subtracted from
the maximum attendance probability for any one health facility found so far.]
overlay x 2 max centre3 temp
[The resultant image is reclassified. Any values less than zero are assigned the serial number
3, whilst values greater than zero are assigned the serial number 0. The output image thus

```


contains the serial number of health centre 3, wherever this has the greatest probability of attendance.]

```
reclass x i temp temp2 2 3 -100 0 0 0 100 -9999
```

[The resultant image (temp2) is superimposed on the image containing the serial numbers of clinics 1 and 2. The serial numbers of clinics 1 and 2 are retained, however, wherever the temp2 image has a value of zero. The result of this operation is therefore an image with the serial number of the facility with the greatest probability of attendance.]

```
overlay x 7 temp2 maxid maxid2
```

[This process continues, until all of the health facilities in Buhera district have been processed.]

```
overlay x 9 max centre3 max2
```

```
overlay x 2 max2 centre4 temp
```

```
reclass x i temp temp2 2 4 -100 0 0 0 100 -9999
```

```
overlay x 7 temp2 maxid2 maxid
```

```
overlay x 9 max2 centre4 max
```

```
..
```

```
..
```

The following program was used to plot lines linking health centres to survey villages. The lines depict the number of growth monitoring visits made by children under 5 years in each of the villages. The program was written in MapBasic, the applications language for the MapInfo 4.0 GIS system.

```
'      PROGRAM WHICH PRODUCES LINES LINKING SURVEYED VILLAGE
LOCATIONS TO HEALTH CENTRES ATTENDED DURING GROWTH MONITORING
'
```

```
Include "MAPBASIC.DEF"
```

```
Dim i, j as integer 'LOOP COUNTER VARIABLES
```

```
Dim healthcentre, tablevillage as integer 'TEMPORARY VARIABLES FOR
STORING THE SERIAL NUMBERS OF VILLAGES AND HEALTH CENTRES
```

```
Dim nrows, nrowsvill as smallint 'VARIABLES FOR STORING THE NUMBER
OF RECORDS IN THE DIFFERENT TABLES USED
```

```
Dim visitline as object 'A SPECIAL GIS FEATURE VARIABLE, USED TO
STORE THE CARTOGRAPHIC LINES DEPICTING THE VISITS MADE
```

```
Dim visitwidth as pen 'A SPECIAL GIS DRAWING STYLE VARIABLE,
USED TO STORE THE LINE STYLE USED TO DENOTE DIFFERENT NUMBERS OF
VISITS ON THE MAP
```

```
Dim x1, y1, x2, y2 as float 'TEMPORARY VARIABLES USED TO STORE THE
START AND END POINTS OF LINES
```

```
Dim foundvillage as logical 'A YES/NO VARIABLE, USED TO IDENTIFY
WHETHER OR NOT A SERIAL NUMBER HAS BEEN SUCCESSFULLY LOCATED IN THE
VILLAGES TABLE
```

```
Dim novisits as integer 'TEMPORARY VARIABLE USED TO STORE THE
NUMBER OF VISITS MADE BY CHILDREN FROM A GIVEN VILLAGE TO A GIVEN
HEALTH CENTRE
```

```
'      OPEN THE RELEVANT MAPINFO TABLES (LOCATIONS OF VILLAGES,
STORED IN villages, AND DETAILS OF GROWTH MONITORING VISITS, STORED
```


IN visitstable) AND CREATE A NEW TABLE CALLED linklines TO STORE THE RESULTS IN

```

Open Table "c:\mapinfo\gpsvill" as villages
Open Table "c:\mapinfo\quest6" as visitstable
Create Table linklines
(was_found logical)
File "c:\mapinfo\mohlink2"
Set Coordsys Earth
Create Map for linklines
nrows=TableInfo(visitstable,TAB_INFO_NROWS)
nrowsvill=TableInfo(villages,TAB_INFO_NROWS)

'
INITIALISE VARIABLES

foundvillage=FALSE

'
READ IN THE INFORMATION FROM THE 'VISITS' TABLE. EACH
ROW IN THIS TABLE CONTAINS DETAILS OF VISITS BY CHILDREN IN A GIVEN
VILLAGE TO A GIVEN HEALTH CENTRE, PLUS A MAP OF RELATED POINTS
REPRESENTING HEALTH CENTRE LOCATIONS.

fetch first from visitstable
x1=objectgeography(visitstable.obj,OBJ_GEO_POINTX)
y1=objectgeography(visitstable.obj,OBJ_GEO_POINTY)
novisits=visitstable.visits
healthcentre=visitstable.village_id

'
FIND THE MATCHING RECORD IN THE VILLAGES TABLE...

fetch first from villages
j=1
tablevillage=villages.villageid
if healthcentre=tablevillage then
    foundvillage=TRUE
    x2=objectgeography(villages.obj, OBJ_GEO_POINTX)
    y2=objectgeography(villages.obj, OBJ_GEO_POINTY)
end if
While (not foundvillage) and (j<nrowsvill+1)
    Fetch next from villages
    j=j+1
    tablevillage=villages.villageid
    if healthcentre=tablevillage then
        foundvillage=TRUE
        x2=objectgeography(villages.obj,
OBJ_GEO_POINTX)
        y2=objectgeography(villages.obj,
OBJ_GEO_POINTY)
    end if
Wend

'
IF A MATCHING VILLAGE IS FOUND, DRAW A LINKING LINE.
VARY THE WIDTH OF THE LINE ACCORDING TO THE NUMBER OF VISITS MADE.

if foundvillage then
    if (novisits < 4) then
        visitwidth=makepen(1,1,BLACK)
    elseif (novisits < 6) then
        visitwidth=makepen(2,1,BLACK)

```



```

        visitswidth=makepen(3,1,BLACK)
    elseif (novisits<10) then
    elseif visitswidth<8) then
        visitswidth=makepen(4,1,BLACK)
    elseif (novisits<12) then
        visitswidth=makepen(5,1,BLACK)
    elseif (novisits<14) then
        visitswidth=makepen(6,1,BLACK)
    else
        visitswidth=makepen(7,1,BLACK)
    end if
    create line
        into variable visitline
        (x1, y1) (x2, y2)
        pen visitswidth
    insert into linklines
        (was_found,obj)
        Values (foundvillage, visitline)
    foundvillage=FALSE
end if

'      NOW DO THE SAME FOR ALL THE OTHER ROWS IN THE TABLE.
READ IN THE INFORMATION FROM THE 'VISITS' TABLE AGAIN.

for i=1 to nrows-1
    fetch next from visitstable
    healthcentre=visitstable.village_id
    x1=objectgeography(visitstable.obj,OBJ_GEO_POINTX)
    y1=objectgeography(visitstable.obj,OBJ_GEO_POINTY)
    novisits=visitstable.visits

'      FIND THE MATCHING RECORD IN THE VILLAGES TABLE

        fetch first from villages
        j=1
        tablevillage=villages.villageid
        if healthcentre=tablevillage then
            foundvillage=TRUE
            x2=objectgeography(villages.obj,
OBJ_GEO_POINTX)
            y2=objectgeography(villages.obj,
OBJ_GEO_POINTY)
        end if
        While (not foundvillage) and (j<nrowsvill+1)
            Fetch next from villages
            j=j+1
            tablevillage=villages.villageid
            if healthcentre=tablevillage then
                foundvillage=TRUE
                x2=objectgeography(villages.obj,
OBJ_GEO_POINTX)
                y2=objectgeography(villages.obj,
OBJ_GEO_POINTY)
            end if
        Wend

'      DRAW A LINE BETWEEN VILLAGE AND HEALTH CENTRE VISITED

        if foundvillage then

```



```

        visitswidth=makepen(1,1,BLACK)
elseif (novisits < 3) then
if (novisits<2) then
visitswidth=makepen(2,1,BLACK)
elseif (novisits <4) then
        visitswidth=makepen(3,1,BLACK)
elseif (novisits<5) then
        visitswidth=makepen(4,1,BLACK)
elseif (novisits<6) then
        visitswidth=makepen(5,1,BLACK)
elseif (novisits<7) then
        visitswidth=makepen(6,1,BLACK)
else
        visitswidth=makepen(7,1,BLACK)
end if
        create line
            into variable visitline
            (x1, y1) (x2, y2)
            pen visitswidth
        insert into linklines
            (obj)
            Values (visitline)
        foundvillage=FALSE
    end if
next
'
MAKE THE NECESSARY CHANGES AND CLOSE ALL OF THE TABLES
\
USED

Commit Table linklines
Close Table linklines
Close Table villages
Close Table visitstable

```


Appendix 3: Interpolation of rainfall data

This appendix describes in greater detail the technique used to interpolate annual rainfall totals from measurements at meteorological stations. As noted in Chapter 6, information about Cold Cloud Duration (CCD) and elevation was used in the interpolation process. The total number of half-hours of CCD was available for each year from 1988 onwards, based on identification of cloud top temperatures below 235 degrees K using the infra-red band of Meteosat 5 (USAID, 1998).

Co-kriging was preferred to other methods of interpolation, such as distance-weighted averaging, for the following reasons:

- it enables several variables apart from rainfall measurements for meteorological stations to guide the interpolation process (in this case elevation and CCD)
- It enables the variance of the estimated values to be calculated at any given point. This gives a measure of the accuracy of the interpolated values.
- It uses a statistical relationship, based on the cross-variogram¹, to interpolate rainfall values, rather than an arbitrary function as is common in distance weighting.

The interpolation procedure was performed using custom-written software produced by FAO (Bogaert et al, 1995) and the Idrisi GIS system. In addition to CCD, elevation, and rainfall data for 52 meteorological stations, elevation and CCD for 208 additional points on a regular grid were used to guide the interpolation. This number of additional sample points represented a compromise between the increased accuracy the interpolation resulting from the inclusion of extra sample points and the computer processing time required to perform the calculations. Any drift in the mean value related to latitude and longitude was eliminated for each of these three variables. This de-trending was performed by fitting a polynomial equation to the data that estimated the value of each variable based on latitude and longitude. The residuals of this equation were then taken as de-trended values and used in subsequent analysis. A variogram was estimated for each variable, indicating how the strength of the relationship between values at neighbouring points changed with distance. Cross-variograms were also estimated for each pair of variables and these indicated how the strength of the relationship between two different variables (e.g. elevation and rainfall) changed with distance. Following the procedure recommended by Bogaert et al (1995: pp 17-18), a

¹ A description of how the strength of the relationship between two variables changes with distance.

combined nugget and spherical model was fitted to each variogram and co-variogram. This fitted model was then used to estimate interpolated values across a regular grid, based on the ten nearest sample points. The output grid, which had a resolution of 0.06 degrees, was exported to the Idrisi GIS, together with an estimate of the standard error for each grid square.

References:

Boegart, P., Mahau, P. and Beckers, F. (1995): 'The spatial interpolation of agro-climatic data'. *Agrometeorology Series Working Paper 12*. FAO, Rome, 60pp.

USAID (1998): <http://nic.fb4.noaa.gov/products/fews/cct.html>

Appendix 4: Chi-square statistics for annual analysis of underweight prevalence

The following chi-square tables accompany the yearly analysis presented in Chapter 6. For all tables, the under-nutrition rate is based on the weight-for-age indicator in children under 5 years and the number of reported cases of disease is also based on children under 5 years only.

Maize yield / % underweight	DECREASE	INCREASE	Total
DECREASE	78	39	117
INCREASE	72	23	95
Total	150	62	212

Table A1: Annual change in under-nutrition rate cross-tabulated with change in maize yields in Communal Areas for Zimbabwean districts, 1988-1993 (Chi-square statistic insignificant at the 95%)

Goat numbers / % underweight	DECREASE	INCREASE	Total
DECREASE	27	25	52
INCREASE	36	26	62
Total	63	51	114

Table A2: Annual change in under-nutrition rate cross-tabulated with change in goat numbers in Communal Areas, SSCFAs, and Resettlement Areas for Zimbabwean districts, 1988-1993 (Chi-square statistic insignificant at the 95%)

Cattle numbers / % underweight	DECREASE	INCREASE	Total
DECREASE	26	26	52
INCREASE	39	23	62
Total	65	49	114

Table A3: Annual change in under-nutrition rate cross-tabulated with change in cattle numbers in Communal Areas, SSCFAs, and Resettlement Areas for Zimbabwean districts, 1988-1993 (Chi-square statistic insignificant at the 95%)

Diarrhoea / % underweight	DECREASE	INCREASE	Total
DECREASE	42	35	77
INCREASE	45	46	91
Total	87	81	168

Table A4: Annual change in under-nutrition rate cross-tabulated with change in reported cases of diarrhoea for Zimbabwean districts, 1988-1993 (Chi-square statistic insignificant at the 95%)

ARI / % underweight	DECREASE	INCREASE	Total
DECREASE	52	25	77
INCREASE	50	41	91
Total	102	66	168

Table A5: Annual change in under-nutrition rate cross-tabulated with change in reported cases of Acute Respiratory Infection (ARI) for Zimbabwean districts, 1988-1993 (Chi-square statistic insignificant at the 95%)

Relief requests / % underweight	DECREASE	INCREASE	Total
DECREASE	48	43	91
INCREASE	34	47	81
Total	82	90	172

Table A6: Annual change in under-nutrition rate cross-tabulated with change in the number of people requesting drought relief for Zimbabwean districts, 1988-1993 (Chi-square statistic insignificant at the 95%)

Appendix 5: District-Level Cross-Correlation Results

District	Average Lead/Lag Statistic			Cross-correlation type		
	Diarrhoea	Malaria	ARI	diarrhoea	Malaria	ARI
Beitbridge	none	1.3	-3.7	U	N	N
Bikita	-2.8	-5.0	1.3	B	P	N
Bindura	none	-1.0	-0.7	U	P	P
Binga	-2.8	none	-2.6	P	U	P
Bubi	-2.8	none	-4.0	P	U	P
Buhera	-1.3	2.4	-6.0	P	B	N
Bulawayo	0.8	none	0.7	P	U	N
Bulili-	0.0	1.0	-1.7	P	N	P
mamangwe						
Chegutu	-1.7	none	3.2	P	U	B
Chikomba	6.0	-4.0	-1.0	P	P	P
Chimanimani	0.0	0.0	0.5	N	P	N
Chipinge	none	-0.1	-6.0	U	B	P
Chiredzi	-0.9	none	3.0	P	U	B
Chirumanzu	6.4	0.6	none	P	P	U
Chitungwiza	none	-3.9	2.1	U	P	N
Chivi	-1.0	none	5.0	P	U	P
Gokwe	-7.0	none	-3.3	P	U	N
Goromonzi	-0.3	none	1.3	P	U	B
Guruve	0.7	none	none	N	U	U
Gutu	5.3	none	-3.0	P	U	N
Gwanda	-1.1	none	-6.0	P	U	P
Gweru	-4.0	4.0	none	P	N	U
Harare	-1.3	-1.0	none	P	P	U
Hwange	none	none	-2.0	U	U	P
Insiza	none	0.0	3.0	U	N	N
Kadoma	0.0	3.0	0.0	P	N	P
Kariba	-1.0	-2.0	4.0	P	P	P
Karoi	-3.0	none	2.4	N	U	N
Kwekwe	-1.0	3.0	-1.3	P	N	N
Lupane	none	-2.0	none	U	P	U

Table A8: District-level average lead/lag statistics for percentage of underweight children against reported cases of diarrhoea, malaria, and Acute Respiratory Infection [ARI] (average lead/lag statistics based on the formula given in Cliff, A. D., Haggett, P., and Ord, J.K. (1986): *Spatial Aspects of Influenza Epidemics*. London: Pion Ltd: p. 195. Cross-correlation types are: U – uncorrelated with % underweight for all lags; P – positively correlated with % underweight for at least one lag; N – negatively correlated with % underweight for at least one lag; B – both positively and negatively correlated with % underweight, depending on the lag considered). Table continued overleaf.

District	Average Lead/Lag Statistic			Cross-correlation type		
	Diarrhoea	Malaria	ARI	diarrhoea	Malaria	ARI
Makonde / Zvimba	5.0	2.0	-3.0	P	N	N
Makoni	-3.0	3.3	none	P	B	U
Marondera	none	1.0	none	U	P	U
Masvingo	none	none	-2.1	U	U	N
Matopo	0.0	3.0	none	P	P	N
Mazowe	6.0	2.7	-3.9	P	N	N
Mberengwa	0.7	none	none	P	U	U
Mount Darwin	2.7	2.8	6.0	P	B	P
Mudzi	-1.0	none	2.0	P	U	N
Murehwa (UMP)	-2.0	none	none	P	U	U
Murewa	none	-7.0	2.0	U	N	B
Mutare Rural	3.2	-4.0	2.2	N	N	N
Mutare City	2.0	-1.0	6.0	N	P	N
Mutasa	1.0	1.0	none	P	P	U
Mutoko	none	none	-6.0	U	U	N
Muzarabani	-5.0	3.2	-3.0	N	B	N
Mwenezi	-1.4	none	-4.4	P	U	B
Nkayi	-0.4	none	0.3	P	U	P
Nyanga	none	none	none	U	U	U
Rushinga	1.5	-1.7	-0.8	B	B	N
Seke	-3.0	none	none	P	U	U
Shamva	1.9	-0.9	2.0	B	B	N
Shurugwi	4.0	-6.0	-3.0	P	P	N
Tsholotsho	-1.5	none	-4.0	P	U	P
Umzingwane	-0.3	none	none	P	U	U
Wedza	7.0	3.0	-3.0	P	B	N
Zaka	1.0	-5.0	none	P	N	U
Zvishavane	0.5	3.3	4.0	P	P	P

Table A8: District-level average lead/lag statistics for percentage of underweight children against reported cases of diarrhoea, malaria, and Acute Respiratory Infection [ARI] (average lead/lag statistics based on the formula given in Cliff, A. D., Haggett, P., and Ord, J.K. (1986): *Spatial Aspects of Influenza Epidemics*. London: Pion Ltd: p. 195. Cross-correlation types are: U – uncorrelated with % underweight for all lags; P – positively correlated with % underweight for at least one lag; N – negatively correlated with % underweight for at least one lag; B – both positively and negatively correlated with % underweight, depending on the lag considered). Table continued from previous page.

Appendix 6: Relevant questionnaires used in the Buhera field survey

Household Assets and Income Questionnaire

Date of Interview (day-month-year) / / Enumerator ID:
 Ward: Vidco: Village Name: _____
 Household Number _____

Enumerator Name: _____
 Field Supervisor (Initials): _____ Date office checked: / /
 Responsible Senior Researcher Initials: _____ Date office checked: / /
 Household Head Name: _____
 Respondent Name: _____
 Relationship of respondent to household head: _____

Qu 1: How many of the following agricultural assets does the household own?

Record the answer of the respondent in the table below using the following instructions and codes.
NAME OF ASSET: Read out the list of agricultural assets.
NUMBER Specify the number of each asset owned by the household. Note: For fence record the total number of rolls used for all the fences. Write '0' if the household does not have a particular asset.
SOURCE FOR ASSETS OWNED: Record how the household obtained each asset: purchased for cash=1; purchased for credit=2; gift=3; bartering=4; inheritance=5; homemade=6; other=00 (specify in the box).
YEAR ACQUIRED: Record the year the household acquired the major assets from 1-9 e.g. 1990.
YEAR SOLD: Specify whether the household sold any of the agricultural assets listed by stating which year they sold them e.g. 1992.
NUMBER SOLD: Record the No. each asset sold since the year acquired (only for those that were sold).
SOURCE FOR ASSETS SOLD: Record how the household obtained each asset: purchased for cash=1; purchased for credit=2; gift=3; bartering=4; inheritance=5; homemade=6; other=00 (specify in the box).

Asset Code	Name of Agricultural Asset	Number	Source for assets owned	Year Acquired	Year Sold	No. Sold	Source for assets sold
01	Maize Sheller						
02	Planter						
03	Scotch Cart						
04	Cultivator						
05	Plough						
06	Harrow						
07	Sprayer						
08	Fence						
09	Wheel Barrow						
****	*****	Remember to record year acquired for the major assets 1-9					
10	Chains						
11	Pick						
12	Mattock						

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Qu 1: (continued) How many of the following agricultural assets do you own?

Asset Code	Name of Agricultural Asset	Number	Source for assets owned	Year Acquired	Year Sold	No. Sold	Source for assets sold
13	Shovel						
14	Fork						
15	Rake						
16	Sickle						
17	Slasher						
18	Hoe						
19	Axe						
00	Other Agri.						

Qu 2: How many of the following household assets does the household own?

Record the answer of the respondent in the table below using the following instructions and codes.

NAME OF ASSET: Read out the list of household assets.

NUMBER: Specify the number of each asset owned by the household. Write '0' if the household does not have a particular asset.

SOURCE FOR ASSET OWNED: Record how the household obtained each asset: purchased for cash=1; purchased for credit=2; gift=3; bartering=4; inheritance=5; homemade=6; other=00; (specify in the box)

YEAR ACQUIRED: Please specify the year when the household acquired the asset e.g. 1990.

YEAR SOLD: Specify whether the household sold any of the agricultural assets listed by stating which year they sold them e.g. 1992.

NUMBER SOLD: Record the No. each asset sold since the year acquired (only for those that were sold).

SOURCE FOR ASSETS SOLD: Record how the household obtained each asset: purchased for cash=1; purchased for credit=2; gift=3; bartering=4; inheritance=5; homemade=6; other=00 (specify in the box).

Asset Code	Name of Household Asset	Number	Source	Year Acquired	Year Sold	No. Sold	Source for assets sold
20	Chairs						
21	Table/s						
22	Gas/Paraffin stove						
23	Wood Stove						
24	Sofa						
25	Display cabinet						
26	Kitchen Unit						
27	Wardrobe						
28	Beds						
29	Radio						
30	T.V.						

Qu 2: (continued) How many of the following household assets does the household own?

Asset Code	Name of Household Asset	Number	Source	Year Acquired	Year Sold	No. Sold	Source for assets sold
31	Sewing machine						
32	Bicycle						
33	Motorcycle						
34	Water cart						
35	Car in running order						
36	Blankets						
00	Other _____						

Qu 3: How many large and small livestock does the household own currently?

List the livestock owned by the household in the table below using the following instructions and codes:-

NUMBER OWNED CURRENTLY: Specify the number owned currently. Do not include loaned animals.

SOURCE OF LIVESTOCK: Specify the source of owned livestock using the following codes: purchased=1; bred from own stock=2; gift=3; bartering=4; inheritance=5; Lobola=6; 00=other. Specify in the appropriate box. Record all sources if respondent gives more than one source.

NUMBER CURRENTLY LOANED: Specify the number of livestock which do not belong to the household but which are currently used by the household.

SOURCE OF LIVESTOCK: Specify the source of currently loaned livestock using the following codes:- from relative=1; from friends/neighbour=2; hired=3; 00=other. Specify in the appropriate box. Record all sources if respondent gives more than one source e.g. 1;3

NUMBER OWNED BEFORE 1991/2 DROUGHT: Specify the number of livestock owned just before the 1991/2 drought.

NUMBER DIED DURING THE DROUGHT: Specify the number of livestock which died during the 1991/2 drought, i.e. the agricultural season Oct. 1991 - Sept. 1992.

Note: Some livestock may not have been affected by the drought record '0'.

Live-stock Code	Livestock	Number currently owned	Source of owned livestock	Number currently loaned	Source of loaned livestock	Number before 1992 drought	Number died 1992 drought
01	Cattle						
02	Oxen						
03	Draft cows						
04	Donkeys						
05	Sheep						
06	Goats						
07	Pigs						
08	Chickens						
09	Turkeys						
10	Rabbits						
11	Pigeons						

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Qu 4: Is the household a member of a livestock co-op?

Yes

No

If 'No' to question 4 go to question 6. If, 'Yes' to question 4 go to question 5.

Qu 5: What type of livestock does the co-op produce? How many does the co-operative have currently?

NUMBER OF LIVESTOCK: Record the number of livestock currently owned by the co-op? If the co-op does not have a particular livestock type record zero=0.

Livestock Code	Livestock	Number of Livestock
01	Cattle	
02	Oxen	
03	Draft cows	
04	Donkeys	
05	Sheep	
06	Goats	
07	Pigs	
08	Chickens	
09	Turkeys	
10	Rabbits	
11	Pigeons	

Qu 6: How much income has the household earned from livestock sales during the last four months? How often does the household generally sell these livestock?

List income derived from livestock sales in the table below using the following instructions and codes:-
NUMBER OF LIVESTOCK: Specify the number of livestock sold in the last four months.
INCOME TOTAL: Specify the total amount of income you received from the sale in \$Z.
INCOME CONTROL: Specify who controls the income using the following codes:-
 controlled by household head=1; controlled by wife of the household head=2; 3=controlled by both household head and wife; other=00 (specify in the appropriate box)
FREQUENCY OF LIVESTOCK SALES: Ask the respondent how often the household sells their livestock. Specify the frequency using the following codes:- weekly=1; monthly=3; annually=3; other=00.

Livestock Code	Livestock sales	No. livestock sold	Total Income (\$Z)	Income control	Frequency of livestock sales
01	Cattle				
02	Oxen				
03	Draft cows				
05	Sheep				
06	Goats				
07	Pig				
08	Chickens				
10	Rabbits				

Thank you very much.

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Demographic Questionnaire

Date of Interview (day-month-year) / /	Enumerator ID:
Ward: Vidco: Village Name: _____	Household Number _____

Enumerator Name: _____
 Field Supervisor (Initials): _____ Date office checked: / /
 Responsible Senior Researcher Initials: _____ Date office checked: / /

Household Head Name: _____
 Respondent Name: _____
 Relationship of respondent to household head: _____

Qu 1 : How many people are resident in this household?

Number of resident household members: _____	(record numerically)
---	----------------------

Qu 2: List the individual members of your household who are resident.

Record the details of each resident household member in the table overleaf. Where there is more than one wife use a separate questionnaire.

ID: Do not write in this column, this will be filled in during post-checking.

FIRST NAME: Record the first name of each resident household member.

SURNAME: Record the surname of each resident household member.

SEX: Enter 'M' for male or 'F' for female.

AGE: Enter how old the household member is in years. e.g. 38. If the household member is under 12 years ask the respondent their date of birth. If the respondent does not know their age but remembers the year they were born then enter this in 'year' section of the date of birth.

DATE OF BIRTH: Ask for the birth certificate or child's health card and enter the day-month-year for all household members under the age of 12 years. Leave this column blank if the respondent is unsure.

RELATIONSHIP TO HOUSEHOLD HEAD: Write in the relationship to the household head using the following words: household head; spouse; first child; second child; third child etc.; grandchild; parent of household head; uncle; aunt; cousin; grandparent; brother or sister of household head; parent-in-law; son or daughter-in-law; brother or sister-in-law; other relative; adopted, foster, or stepchild; not related.

MAIN INCOME ACTIVITY: Use the following codes: farmer=1; labourer=2; public service=3; business=4; food for work=5; miner=6; local income generating activity (e.g. basket making)=7; school child=8; not an income earner=9; other=00 (specify in box).

EDUCATIONAL LEVEL: Record the educational level attained for each household member e.g. Grade 1; Standard 4; Form 3. If the household member has had no schooling write zero=0.

SCHOOL: For those currently attending a school, write in the name of the school they attend. Distinguish between primary (P) & secondary (Sec) e.g. Chapanduka P, St John's Sec.

RELIGION: Record the religion of each household member using the following codes:- Roman Catholic=1; Anglican=2; Methodist=3; Dutch Reformed=4; Zionist=5; Apostolic Faith=6; Salvation Army=7; SDA=8; Tradition=9; Not sure/won't say=10; Other=00 (Specify in box)

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Name of Household Head: _____

Wife No. _____

ID	First name	Surname	Sex	Age (Yrs)	Date of birth	Relationship to household head	Income activity	Educational Level attained	School currently attended	Religion
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					
					/ /					

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Qu 3: How many houses/huts/housing units does the household have?

Number of household units: _____ (record numerically)

Qu 4: How many rooms are there in each household unit? What are the roofs, walls and floors of each household unit made from? What is the purpose of the household unit? For household units which are used for sleeping how many household members usually sleep in each?

Look at the individual house/huts/housing units and complete the table below, using the following instructions and codes. Note: If the interview is not being carried out in sight of the house, ask the respondent what they are made from.

NUMBER OF ROOMS:- Ask the respondent how many rooms there are in each household unit.

PURPOSE OF HOUSING UNIT: Ask the respondent what purpose the household unit is used for. Use the following codes: Cooking=1; Preparing food=2; Eating=3; Sleeping=4; Bathroom=5; Toilet=6; Storing grain=7; Other storing not grain (e.g. tools)=8; Not in use=9; Other=00 (specify in the box).

NB: If the hut is used for more than one purpose put the relevant codes e.g. 1; 3.

ROOF: Use the following codes to describe the roof of each hut, if more than one material is used record the relevant codes: Thatch=1; Corrugated iron=2; Asbestos=3; Mud=4; Tile=5; Concrete=6; Not roofed=7; Other=00 (specify in the box).

WALL: Use the following codes to describe the walls of each hut, if more than one material is used record the relevant codes: Clay brick=1; Mud=2; Wood=3; Dung=4; Cement=5; Stone=6; Other=00 (specify in the box).

FLOOR: Use the following codes to describe the floors of each hut, if more than one material is used record the relevant codes: Earth/mud/sand=1; Wood=2; Cement=3; Dung=4; Stones=5; Other=00 (specify in the box).

NUMBER OF PEOPLE (SLEEPING): For each household unit which is used for sleeping ask the respondent how many household members usually sleep in it.

Household Unit No.	No. Rooms	Purpose of household unit	Roof	Walls	Floors	No. People using housing unit for sleeping
1						
2						
3						
4						
5						
6						
7						
8						
9						

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Qu 5: What toilet facilities does the household use?

Read out the list of toilet facilities. If the respondent mentions more than one type, tick those that are relevant.

01 Pit/trench latrine	02 Blair	03 Bush	04 Bucket
05 Flush	00 Other (Specify): _____		

Qu 6: What type of fuel does the household use for cooking?

Read out the list of fuel types. If the respondent mentions more than one source, tick those that are relevant.

01 Wood	02 Paraffin	03 Gas	04
Electricity			
05 Charcoal	06 Cow dung		
00 Other (Specify): _____			

Qu 7: What kind of lighting does the household use?

Read out the list of lighting sources. If the respondent mentions more than one source, tick those that are relevant.

01 Home-made Paraffin lamp	02 Commercially made Paraffin Lamp
03 Candles	04 Firewood
05 Gas Lamp	06 Electricity (solar)
07 Electricity (generator)	08 Electricity (ZESA)
00 Other (Specify): _____	

Qu 8: Where does the household get its water for drinking and cooking? Which months does the household usually use this water source?

START MONTH: Enter the month when the household starts using the water sources in the row 'Start month'. Use the following format for writing in months: Jun., Aug., etc.
END MONTH: Record the month when the household stops using the water source in the row 'End Month'. If the household uses the water source all year round write 'all year' in the 'start month' box.
Note: The household may use more than one source of water at any one-time

	Piped water inside	Piped water outside	Comm -unal tap	Protected well or borehole	Unprotected well	Collect rain water	River, stream, lake, or dam	Other specify: _____
Start month								
End month								

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If the household does not change its water source the Demographic Questionnaire is complete. If the household does change its water source ask question 9.

Qu 9: Does the household experience any problems when changing water source?
(a) From wet to dry season

01 Yes Response	02 No	03 Not sure	04 No
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(b) From dry to wet season

01 Yes	02 No	03 Not sure	04 No Response
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If 'Yes' to either question 9a or 9b go to question 10. If 'No', 'Not sure' or 'No Response' to both question 9a and 9b the Demographic Questionnaire is complete.

Qu 10: What problems does the household experience when changing from one water source to another? When are these problems most critical? (specify critical period in months).

PROBLEMS: Use the following codes to classify the problems mentioned by the respondent.
Takes more time-queing=1; Takes more time-walking=2; Use unclean water=3;
Household members suffer from diarrhoea=4; Use less water=5; Other=00 (specify in the box).
Don't read out the list and be sure to enter in any other reasons which the respondent gives.
CRITICAL PERIOD: Specify the critical period in months using the following format e.g. From Jan. to March.

Problems	Critical Period
	From: _____ to: _____
	From: _____ to: _____
	From: _____ to: _____
	From: _____ to: _____
	From: _____ to: _____
	From: _____ to: _____
	From: _____ to: _____
	From: _____ to: _____
	From: _____ to: _____

Additional question asked in the second round of the Demographic Questionnaire:

Where is each under 5 being weighed? Why was the under 5 taken to each particular weighing centre used?

WHERE WEIGHED?: Name the health facility where the <5 yr old has been taken to be weighed. **Note:** If the <5 was weighed at more than one facility name each facility in the separate boxes i.e. facility 1, facility 2.

REASONS FOR TAKING UNDER 5 TO EACH FACILITY: Ask the respondent why each particular facility was used: Use codes to record response:- Closest facility to household=1; on bus route=2; where friends and neighbours take their children=3; good health staff=4; facility open/available on a day when adult carer able to take child=5; facility open/available at a time when adult carer able to take child=6; other=0 (specify)

Child ID Code	ID:	ID:	ID:
Name of child			
Where weighed? Name of facility 1			
Reason for taking to facility 1			
Name of facility 2			
Reason for taking to facility 2			
Name of facility 3			
Reason for taking to facility 3			

Health Status (Morbidity) Questionnaire

Date of Interview (day-month-year) / /	Enumerator ID:
Ward: Vidco: Village Name: _____	Household Number
Enumerator Name: _____	
Field Supervisor (Initials): _____	Date office checked: / /
Responsible Senior Researcher Initials: _____	Date office checked: / /
Household Head Name: _____	
Respondent Name: _____	
Relationship of respondent to household head: _____	

Qu 1: List the individual members of your household who are resident and under the age of 5 yrs. (NB: If there are no < 5 yrs resident in the household record N/A across the table. Go to Qu 2)

Record the details of each resident household member under 5 years. Ask the following questions and take information from the child health card. N.B. Where possible ask the mother of the child.

CHILD ID CODE: Do not write in this column, this will be filled in during post-checking.

NAME: Record the first name of each resident household member under 5 years.

SURNAME: Record the surname of each resident household member under 5 years.

SEX: Enter 'M' for male or 'F' for female.

DATE OF BIRTH (D.O.B.): Date of birth enter day-month-year using the child's health card or birth certificate only. If the mother knows the date of birth fill in the month & year section only. If these are not available record NR across the D.O.B.

MOTHER'S FIRST NAME: Use the household list and ask the respondent for the biological mother. Record the biological mother's first name.

MOTHER'S AGE / D.O.B.: Use the household list & record age or date of birth of biological mother.

MOTHER'S ID CODE: Do not write in this column, this will be filled in during post-checking.

REPEAT THE ABOVE FOR BIOLOGICAL FATHER

PLACE OF BIRTH: Use the following codes: At home=1; Rural health clinic=2; Rural hospital=3; District Hospital=4; Mission/Mine hospital=5; Urban hospital=6; Other=00 (specify).

Note: If a health facility was used record its name in full e.g. 2; Mombayarara rural health clinic.

BIRTH WEIGHT: Read the health card and specify birth weight in grams. e.g. 2800g

IMMUNISATION STATUS: Read the health card and indicate against each vaccine the number of doses each child has received. E.g. M1= (one measles); Record '0' if the vaccine has not been given.

TOTAL NO. TIMES WEIGHED FROM 1 MTH TO 12 MTHS OF AGE : Use the health card & count up how many times the child has been weighed between 1st month of life to 12 mths. Record the response numerically e.g. 3

TOTAL NO. OF TIMES WEIGHED FROM 13 MTHS TO 24 MTHS: Look at health card & count up how many times child has been weighed between 13-24 mths. Record response numerically e.g. 4

NUMBER OF TIMES THE CHILD WAS THE SAME WEIGHT OR LESS WEIGHT THAN PREVIOUS WEIGHING: Look at the health card, count how many times the child remained the same weight or decreased in weight since the previous weighing. Record the response numerically e.g. 3

POSITION IN FAMILY: First child =1; Second child =2; etc. (If the third birth results in twins write 3a & 3b). **Note:** Position in family refers to the mother's first child rather than the father's.

STILL BREAST FEEDING ONLY: Ask the respondent if any of the < 5 yrs are being breast fed ONLY. Use the codes:- Breast fed only=1; Breast fed and water=2; Breast fed and given solid foods=3; Weaned (solid foods only not being breast fed=4; Other=00 (specify)

AGE SOLID FOOD INTRODUCED: Ask the respondent the age in months when solid food was first given to each of the < 5yr listed. Use the following abbreviations in front of the age in months to denote approximate age 'LT'=less than; 'MT'=more than. Record the answer numerically e.g. MT 5 mths. If no solid food introduced record N/A. If month unknown record N/R.

NUMBER TIMES FED YESTERDAY: Ask the respondent the number of times each child under 5 years was fed yesterday. Record the response numerically e.g. 3

Child ID Code	ID:	ID:	ID:	ID:	ID:
First name of child					
Surname of child					
Sex					
DATE OF BIRTH (D.O.B.)	/ /	/ /	/ /	/ /	/ /
Mother's first name					
Mother's Age or D.O.B.					
Mother's ID Code	ID:	ID:	ID:	ID:	ID:
Father's first name					
Father's Age or D.O.B.					
Father's ID Code	ID:	ID:	ID:	ID:	ID:
Place of birth/Name of Health Facility					
Birth weight (grams)					
Immunisation Status	BCG P DPT M DT	BCG P DPT M DT	BCG P DPT M DT	BCG P DPT M DT	BCG P DPT M DT
Total No. times weighed in first year of life					
Total No. times weighed in 2nd year of life					
No. times child same weight or less weight than previous weighing					
Position in family					
Still breast feeding only					
Age solid food intro.					
No. times fed yesterday					

Qu 2: Has any resident member of the household been ill in the last 2 weeks?

If No household member was in ill during the last two weeks write N/A across the table below. If one or more household members were ill during the last two weeks, use the instructions to fill-in table.

ID: Leave this column blank. Do not write in this column.

FIRST NAME & SURNAME: Record the first name and surname for each household member who has been ill during the last two weeks.

'ILLNESS': Record the name of the illness in the 'Illness' column. **Examples of illnesses include:** diarrhoea, worms in stools, blood in urine, bilharzia, fever attacks, headache, malaria, measles, bad coughing, coughing up blood, cold/flu, eye problem, ear problem, teeth problem, vomit, fracture, concussion, bite, burn. If the respondent does not know name of illness put 'ill' do not guess illness from symptoms given from the respondent. **NB: If a household member suffers from more than one illness or symptom record all the symptoms in same the box.**

'ILLNESS ID': Leave this column blank.

NUMBER OF DAYS SICK: Record the number of days when the member was ill or how many days the member has been ill so far in 'No. Days Sick' column. If the household member has suffered from more than one symptom add up all the days lost. Use 'MT' as an abbreviations in front of the number of days to denote if more than 14 days **NUMBER OF DAYS LOST AT WORK/SCHOOL:** Record the number of work or school days lost as a result of the illness in the 'days lost at work/school' column.

Note: (work is defined as main income activity). For young children who are unable to work because of their age record N/A.

NUMBER OF DAYS UNABLE TO CARRY OUT HOUSEHOLD CHORES: Record number of days unable to carry out household chores as a result of the illness in the 'No. Days unable to carry out household chores' column. For young children who too young to work record N/A.

ID	First Name:	Surname:	Illness	Ill ID	No. Days Sick	No. days lost at work/ school	No. Days unable to carry out household chores

Qu 3 : Did any resident household members go to a health facility during the past two weeks?

Ask the respondent if any household member went to a health facility (hospital, clinic, outreach centre) during the past two weeks. Tick the appropriate box below.

Yes	No	Not sure	No Response
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If 'No', 'Not sure' or 'No response' go to question 5. If 'Yes' go to question 4.

Qu 4: What are the names of resident household members who attended a health facility in the last two weeks?

For household members who attended a health facility fill in the chart below using the following instructions:-

ID: Leave this column blank. Do not write in this column.

FIRST NAME AND SURNAME: Record the name of those household members who attended a health facility in the last two wk's.

NAME OF HEALTH FACILITY: Record the name of the health facility e.g. Murambinda district hospital.

REASON FOR ATTENDANCE: Use following codes:- growth monitoring programme=1; immunisation=2; pregnant=3; ill health=4; 00=other

TREATED BY: Use the following codes: doctor=1; nurse=2; trained midwife=3; village health worker=4; traditional midwife=5; 00 = other.

OUTPATIENT?: Was the household member treated as an outpatient or were they admitted? Use following codes:- outpatient=1; admitted=2.

DAYS IN HOSP: Record the number of days each household member who was admitted, spent in hospital.

HEALTH FEE: Record the cost of health fee in (Z\$). If the health fee includes medicines write HF/M before the cost e.g. HF/M \$10. The health fee does not include medication write HF only e.g. HF \$7.50. **Note:** If, the health fee was free enter '0'.

MEDICINE NEEDED?: Ask the respondent if the household member need medicine & was this available? Use the following codes:- medicine not needed=1; medicine needed & available=2; medicine needed but not available=3; medicine available but unable to pay=4; other=00 (specify)

COST OF MEDICINES: Record the cost of medicines in (Z\$). If, free enter '0'.

TYPE OF TRANSPORT USED: Enter the following codes for the type of transport used to get to the health facility: walk=1; bus=2; bicycle=3; scotch cart=4; wheel barrow=5; hitched a ride=6; own car=7; 00 = other (specify).

TRAVEL TIME: Enter the time taken to travel to the health facility using the following abbreviation to denote if hours or minutes (hrs./mins) e.g. 30 mins; 2 hrs.

COST OF TRAVEL TO HEALTH FACILITY: Enter the cost of travelling to and from the health facility, e.g. \$1.50. If free enter '0'. Other= 00 (Specify)

ID	First Name:	Surname:	Name of health facility	Reason for attendance	Treated by	Out-patient?	No. days in hospital	Health Fee (Z\$)	Medicine needed	Cost of medicine (Z\$)	Type of transport used	Travel Time (hrs/ mins)	Cost of travel (Z\$)

Qu 5: Did any resident household member who needed medical attention in the past two weeks, not visit a formal health facility?

Yes

No

No response

If 'No' or 'No response' go to question 7. If 'Yes' go to question 6.

Qu 6: Why did the resident household member(s) who needed to visit a formal health facility in the past two weeks not visit one?

Use the following instructions to fill in the table below:-

FIRST NAME AND SURNAME: Record the first name and surname of the household member(s) who did not visit a health facility but needed medical assistance.

REASON FOR NON-ATTENDANCE: Health facility too far away=1; Lack of money=2; Too ill to travel for treatment=3; Religious beliefs=4; Mistrust of health services=5; Other=00 (specify)

ID	First Name:	Surname:	Reason for non-attendance

Qu 7: Was any resident household member treated by any of the following in the last two weeks.

Ask the respondent if any resident household member was treated by any of the following in the last two weeks. Tick the appropriate box.

	Yes	No
Traditional Healer		
Religious Healer		

Qu 8: Has the household received, seen, or heard any information on Health Education (Family planning, hygiene, water) or Nutrition (Food and Health) in the last 4 months. Is this information useful?

Ask the respondent if the household has received any information on Health Education or Nutrition.
RECEIVED: Use the following codes:- received=1; not received =2;
USEFUL: Use the following codes:- Useful=1; Not useful=2; Not sure=3; 00=other (specify)
SOURCE: Where did you get the information? Use the following codes to explain the source of information: radio=1; T.V.=2; doctor=3; nurse=4; village health worker=5; village development worker=6; school=7; neighbours/friends=8; newspapers/magazines=9; poster=10; rallies/meetings=11; NGO=12 e.g. Christian Care; Ordely =13; Health worker= 14; 00=other (Specify).

Type of Information	Received	Useful	Source
Health Education & Nutrition			

Qu 9: Has any member who was resident in the household died in the last four months?

Yes	No	No response
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If 'yes' go to Question 10. If 'No' or (and) 'No response' the questionnaire is complete.

Qu 10: What was the cause of death of the resident household member(s) who died in the last four months?

REMEMBER TO ASK THIS QUESTION VERY SENSITIVELY.
HOUSEHOLD MEMBER ID: Leave this column blank. Do not write in this column.
FIRST NAME & SURNAME: Record the first name and surname of the dead household member.
AGE or DATE OF BIRTH (D.O.B.) : Ask the respondent the age or date or birth of the household member who has died in the last four months.
CAUSE OF DEATH: Ask the respondent the cause of death. Write the cause in the appropriate box. Accept what the respondent states.
LENGTH OF ILLNESS: Use the following codes to classify how long the person was ill before they died:- short term illness=1; (less than 3 months) ; long term illness=2; (i.e. more than three months); accident=3; 00=other (specify).

ID	First Name:	Surname:	Age or D.O.B.	Cause of Death	Length of illness

Appendix 7: Publications resulting from the thesis

Wright, J.A., Gundry, S.W., Ferro-Luzzi, A. and Hoyles, P.J. (1997): 'Validation of a Complex Spatial Model of the Food and Nutrition System in Zimbabwe'. Proceedings, *ModSim 97, the International Congress on Modelling and Simulation*, Hobart, Tasmania. 8-11 December, 3: 1057-1062.

Wright, J.A., Gundry, SW, Ferro-Luzzi A, Hoyles PJ, Vaze, PB, Nyatsanza J & Dent JB (*in press*): 'Identifying temporal and spatial trends in growth monitoring data and the links to socio-economic and environmental variability in Zimbabwe'. *Ecology of Food and Nutrition*. © OPA (Overseas Publishers Association), Amsterdam, BV.

Validation of a Complex Spatial Model of the Food and Nutrition System in Zimbabwe

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Abstract. This paper describes a method of validating a complex model of the food system in a district of Zimbabwe. The model will simulate patterns of malnutrition in all households within the district, using an artificial population created from census information and a sample survey. Model validation should require use of an independent data set not used in model construction. In many cases, such data are based on non-standard spatial units and may also be prone to bias. For the study district, the only nutritional data available are anthropometric measurements of children attending health centres, rather than district-wide household surveys. To use such data for validation, an attendance model has been developed that assesses the likelihood of children taking part in this health centre measurement programme. The probability of a given child being measured at a given facility is estimated based on the type of health facility, the characteristics of the child's household, the distance between the two, and the proximity of other equivalent types of facility. This relationship is estimated using logistic regression on field survey data and then applied to all of the households in the artificial population. The number of children attending each health facility can therefore be estimated, giving figures directly comparable to the aggregated health centre statistics. Incorporation of a module to simulate healthcare uptake means that aggregated model results can be validated for the youngest population cohort. Conditions in past years can be replicated within the model and output compared to historical records for different health centres across the district. This approach could also be applied to data collected at other types of fixed service point in rural areas, such as livestock diptanks, grain depots, or food aid distribution points. This work illustrates how secondary data, based on non-standard spatial units, can still be used for model validation.

1. INTRODUCTION

This paper addresses two problems commonly encountered in developing models of social behaviour. The first problem is the way in which the scale of observation influences the functional form of a given model. Perceived causes of phenomena at household level do not always coincide with those apparent in aggregate data for different social groups or regions. Several studies, for example, have illustrated how the apparent causes of disease clusters change with increasing levels of data aggregation [Waller and Turnbull, 1993; Schneider et al, 1993]. Such difficulties may also occur when analysing geographical patterns of under-nutrition.

The second problem concerns the issue of model validation that has been well documented in the past. Dent and Blackie [1979, pp. 100-102] have suggested four types of data that can be used for validating a model: historical data used in model construction; historical data not used in model construction; historical data collected since the model was constructed; and data explicitly collected for model validation. They suggest that the latter two types of data are more appropriate for validation, but admit that data collection solely for model validation is expensive. These two problems are addressed here by developing a model of health centre attendance based on detailed, household-level data. Aggregated data for each health centre – collected at a different scale – are then used to validate the model.

This approach to model validation is considered here in the light of an analysis of patterns of healthcare uptake in Zimbabwe. A simulation model is developed of participation by young children in a growth monitoring programme in the Buhera District in Manicaland Province. Factors affecting participation in the growth monitoring programme are identified on the basis of a household survey. This household-level model of attendance is then used to estimate the number of children weighed in the district's health centres. Simulation results are then compared to government statistics on the number of children attending each health centre, thereby validating the model using an 'unseen' data set.

1.1 The Growth Monitoring Programme in Zimbabwe

Since 1987, Zimbabwe has been operating a National Health Information System (NHIS) which collates information collected at health centres throughout the country [Tagwireyi and Greiner, 1994]. Part of the information collected through this system concerns the nutritional status of pre-school children, who have their age and weight recorded at health centres as part of a growth monitoring programme. The numbers of children who are weighed and the proportion who are underweight for their age are computerised under the NHIS, but details about the environment which the children come from are not recorded. This lack of information about the children's background makes it difficult to identify the causes of high levels of malnutrition at a particular clinic, without recourse to community-based nutritional surveys of individuals. However, the NHIS growth monitoring data can still be used to validate a model derived from a community-based survey, *provided* that the NHIS data are adjusted to take account of different levels of participation in the weighing programme.

1.2 A Survey of Growth Monitoring Participation and Nutrition

A community-based field survey investigating patterns of healthcare use was undertaken in Buhera District in Manicaland province. Such a survey can be used both to identify the causes of under-nutrition and to assess the

factors that influence participation in the growth monitoring programme described above. Buhera district consists of medium to low potential agricultural land, with annual rainfall varying from around 850 mm in the north to 550 mm in the south. Large rivers, the Save and the Nyazvidzi bound the district on two sides, and these barriers reduce the degree of interaction with neighbouring districts. Subsistence agricultural production is generally insufficient to meet requirements, so many adults work outside of the district in cities, mines or commercial farms, migrating on a seasonal basis and remitting funds back to the household. In terms of health facilities, the district is served by two fully equipped hospitals - Murambinda Mission hospital located in the north of the district, and Birchenough Bridge hospital in the south. Both hospitals lie close to tarmac roads, but there are only dirt roads in the remote, central part of the district. As well as the two main hospitals, the district contains nineteen smaller rural hospitals and clinics with more limited facilities. Schools and settlements in remoter parts of the district are also visited by mobile medical teams once a month, who perform immunisations, growth monitoring, and disseminate health information. Information about the socio-economic characteristics of households in the district is available from the 1992 Zimbabwean national census, broken down into 36 wards [Government of Zimbabwe, 1994].

354 households in 60 different villages within this district were selected to participate in the survey, based on a random sampling plan, stratified to capture variation in access to healthcare [Wright et al, 1996]. This represented a 1% sample of the total district population. The locations of participating villages and local health centres were recorded using a Global Positioning Systems (GPS) receiver and entered onto the GIS system.

2. A HOUSEHOLD MODEL OF GROWTH MONITORING UPTAKE

2.1 Methodology

In October 1995, adult carers of 284 children were asked to identify which clinics or hospitals (if any) their children had visited for growth monitoring. At the same time, the weights and heights of all household members

participating in the survey were recorded. Initial investigation of the response to this question suggested that attendance at the two main hospitals followed a very different pattern from attendance at the other types of health centre. Two separate models of growth monitoring attendance were developed for these two types of facility, in which attendance at a particular health centre was expressed as a function of:

- the characteristics of the child and the child's family;
- the characteristics of the health centre;
- the distance from the child's home to the health centre
- and the extent to which other neighbouring facilities were able to offer similar facilities.

More formally, this relationship was expressed as a logistic regression equation, such that:

$$P = 1/(1 + e^{-Z}) \quad (1)$$

(where P is the probability of a given child visiting a given health centre and e is the base of natural logarithms).

In this expression, Z is given by the equation:

$$Z = \beta_0 + \beta_1 X_1 + \dots + \beta_n X_n + \epsilon \quad (2)$$

(where $X_1 \dots X_n$ are terms representing the characteristics of the health centre, household and child, the distance from the child's home to the health centre, and competition from other health facilities; and ϵ is a residual error term).

This approach is derived from Rosenberg and Hanlon's [1996] study of healthcare uptake in Ontario, Canada. This study used logistic regression to model general uptake of health services based on demographic, income, and the health service environment, though attendance at specific facilities was not considered. The characteristics of the child and its household included in the analysis were restricted to those that could be obtained from the 1992 census for all the wards in Buhera District. Although this meant that some potentially useful predictors of formal healthcare participation were not considered, it meant that the results of the analysis could be applied to the whole district population by

using the census information. Household characteristics considered in the analysis included the type of water source used, type of sanitation, and type of housing (a proxy measure for wealth).

Distances between surveyed villages and health centres were calculated in such a way that the effect of roads, rivers, and terrain on movement was explicitly incorporated. This was achieved through the use of a 'pushbroom' algorithm, which calculates distances from a 'difficulty of movement' map, rather than taking simple Euclidean distance [Eastman, 1989]. Slopes were calculated from a Digital Terrain Model of the district and converted to difficulty of movement based on human energy expenditure figures for different types of terrain [James and Schofield, 1990]. This was then combined with maps of difficulty of movement along roads and across rivers, derived from a series of interviews with local government staff from within the district (see Wright et al [1996] for a more comprehensive discussion of this procedure).

The extent to which other neighbouring health facilities influenced attendance at a given health centre was represented through a 'competition' variable. Competition was represented by subtracting the distance to the nearest health facility capable of providing the same level of healthcare from the distance to the particular health facility being considered. The value of this competition variable was therefore zero for the nearest facility to a given village, and increased for facilities that were further away. Since the number of possible combinations of independent variables was large, a stepwise regression technique was used to identify the combination of variables that best explained the observed pattern of clinic attendance.

2.2 Household-Level Model Results

Table 1 shows the results of the stepwise logistic regression analysis for hospitals and rural hospitals/clinics. In the case of hospitals, growth monitoring participation was related to the type of water source used by households and to the distance between the survey village and the hospital. The probability of visiting a hospital declined with distance, whilst households using unsafe water sources (such as rivers or dams) were less likely to take their children for growth monitoring. For the

smaller rural hospitals and clinics, the probability of growth monitoring attendance was related solely to the 'competition' variable discussed earlier. The fact that the 'competition' variable proved important for clinics and rural hospitals but not for the main hospitals may be related to the much lower density of main hospitals. Because the main hospitals are so far apart, it may be that they never effectively compete for patients - unlike the clinics and rural hospitals.

Variable	Type of facility	Sig n:	Significance
Distance	Hospital	-ve	**
Water	Hospital		*
Access			
Constant	Hospital	+ve	*
Competition	Clinic	-ve	**
Constant	Clinic	+ve	**

Table 1: Results of Logistic Regression Analysis for Hospitals and Clinics (** = significant at the 99% level; * = significant at the 95% level. The hospital model Chi-square was 128.0 which was significant at the 99.9% level, and the clinic model Chi-square was 163.0, also significant at the 99.9% level¹).

3. SIMULATION OF HEALTH CENTRE ATTENDANCE

In order to validate this relationship, these household-level findings were used as the basis for a simulation that estimated attendance at health centres throughout Buhera. Spatial relationships were important in the model, being represented by the distance and competition terms discussed in Section 2. However, information about the distribution of population was limited. The total number of children under 5 years living in each of the district's 36 wards was available from the August 1992 census [Government of Zimbabwe, 1994]. In addition, the locations of three types of major settlements were available from the local government authorities within the district: growth points (towns with electricity and telephone services), business centres (large villages), and rural service centres (smaller villages). Older, more detailed settlement maps dating from the period of the Rhodesian Unilateral Declaration

of Independence were found to be out of date, confirming the dynamic nature of human settlements in the district noted elsewhere [Campbell et al, 1989]. The under-5 population of a number of rural service centres and business centres was estimated based on a rapid rural appraisal during 1995. In order to create a population density map, the mean number of children estimated as resident was assigned to each rural service centre and business centre in the district. The residual under-5 ward population not accounted for by these major settlements was distributed amongst villages randomly located within the ward.

The model described in Section 2 was then applied to every child in the district. The probability of attendance for each individual was calculated based on type of water source and distance for hospitals, and on the competition variable for clinics. The mean number of children attending each health facility was then calculated by multiplying these probabilities by the number of children at each point in the district.

The questionnaire survey had asked whether or not children under 5 years old had attended health centres, without considering the frequency of visits or the period of time during which the visits took place. Consequently, two adjustments were made so that monthly attendance at health centres could be estimated using the method described above. The questionnaire asked about attendance during a child's lifetime, rather than over a specified period. To compensate for this, the estimated number of visits from the simulation was divided by the average age in months of children in the under-5 age cohort (29 months) to convert to a monthly figure. In addition, the questionnaire considered which health centre a given child had attended, but not the frequency of visits to that health centre. Government of Zimbabwe [1988] note from an extensive national survey of growth monitoring attendance that children on average make four visits in their first year of life, two in their second, and one in their third. The mean number of visits declined further in the fourth and fifth years, as fewer visits to health centres were needed for immunisation. To incorporate the frequency of visits, the number of simulated visits was then multiplied by the mean frequency of visits by children under 5 (6.4 visits). This gave an estimated mean monthly attendance

¹ The model Chi-square is equivalent to the F test for ordinary linear regression.

figure that could be directly compared to the data from the NHIS.

To validate these results, the number of children attending growth monitoring at each health centre per month, averaged over the period January 1990 to September 1995 was then calculated from the NHIS data. Simulation output was then regressed on these actual attendance figures. Following the approach adopted by Kleijnen and Van Groenendaal [1992], an intercept term significantly different from zero was taken as evidence for rejecting the model. Similarly, a slope coefficient significantly different from one would also be taken as evidence for rejecting the model. These two assumptions can be tested simultaneously through the use of an F-statistic [Harrison, 1996], as given by the formula:

$$\frac{(n-2)\{nb_1^2 + 2nb_1(b_2 - 1) + \sum x_t^2(b_2 - 1)^2\}}{2ns^2}$$

where n is the sample size, s^2 is the residual variance, b_1 is the regression intercept coefficient, b_2 is the regression slope

coefficient, and x_t is the t th observation of the real system output.

4. RESULTS AND DISCUSSION

Table 2 shows the results of regressing the real-world data on the simulated numbers of visits. The household-level model failed the validation test, both when all health centres were included and when health centres likely to be visited by children from outside the district were excluded. The regression, which was based on 21 health centres, had an adjusted R^2 of 0.528. When T-tests were applied to the results in Table 2, the constant term was found to be significantly different at the 99% level from zero and the slope coefficient was found to be significantly different from one at the 99% level (although it was significantly different from zero). The model also failed a simultaneous F-test of goodness of fit when this was applied to the regression statistics.

<i>Term</i>	<i>Coefficients</i>	<i>Significance</i>
Intercept	112.7056	99.5%
Slope	0.332552	99.5%

Table 2: Results of regressing real world data on model output.

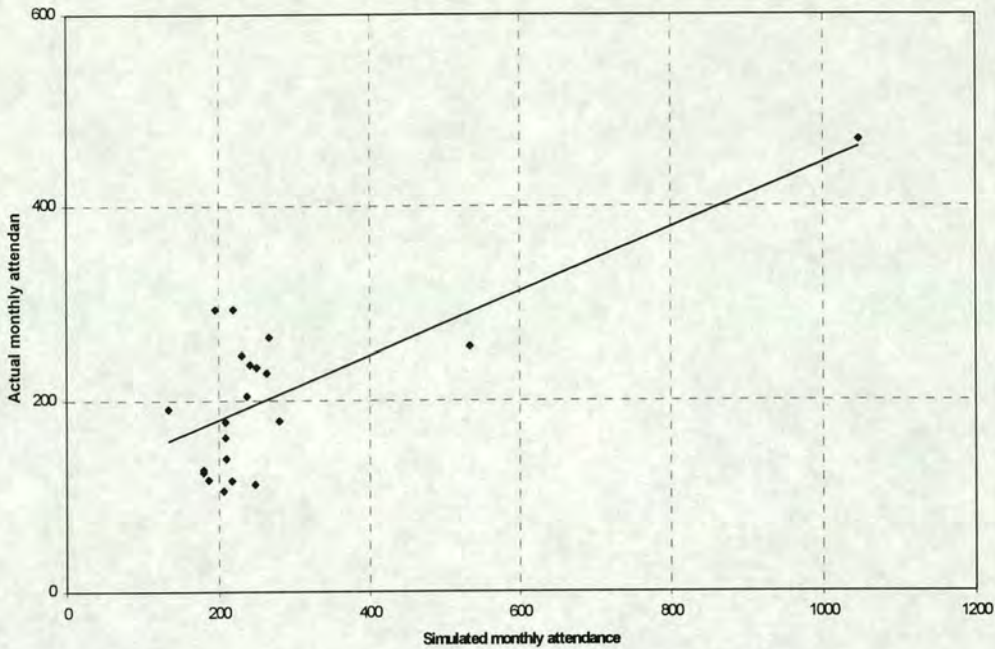


Figure 1: Scatterplot of actual mean number of children under 5 attending growth monitoring per month for 21 health centres and the simulated number attending (the fitted regression line is also shown).

Figure 1 shows the relationship between actual monthly clinic visits and the clinic visits simulated by the model. Although the simulation model successfully predicts a major difference between the number of attendees at the principal district hospital, Murambinda, and the other health centres, it is less successful at discriminating differences between attendance at other clinics.

Several sources of variation that reduce the goodness of fit between the model output and actual attendance figures can be identified:

- Variation associated with the estimation of attendance behaviour from the household survey data;
- Variation associated with the creation of the population density map for the district;
- Variation associated with the rescaling of the simulation results to take account of the frequency of visits by children;
- The confounding influence of visits by children from outside the district, although this is reduced for much of the area by the natural barriers of the Save and Nyazvidzi rivers;
- Transcription, data entry, clerical, and other errors associated with the collation of the NHIS actual attendance figures.

Given these five different sources of variation, the fact that the simulation exercise failed the simultaneous F-test is unsurprising. However, the fact that the simulation model tended to over-estimate attendance suggests that the rescaling adjustment to account for the frequency of health centre use is one of the major sources of error in the model. A revised questionnaire design, asking about frequency of attendance over a specified period, would resolve this difficulty.

In addition, several authors have argued that the simultaneous F-test is too rigorous for agricultural and socio-economic model development. Some have questioned its use with large validation data sets [Thornton and Hansen, 1996], whilst Harrison [1990: p. 183] has suggested that instead: ‘descriptive statistics and subjective tests be used to build up confidence in a model as it proceeds through a number of prototypes’. The scatterplot presented in Figure 1, and the significant, positive slope coefficient identified in the regression exercise both suggest that output from this early prototype of a clinic attendance type is well correlated with actual attendance figures.

5. CONCLUSION

Health centre-level data were used to validate a household-level model. The household-level model failed a regression-based validation test, but was able to distinguish between poorly attended clinics and well-attended hospitals. The attractiveness of hospitals to patients is thus borne out both by the household survey and by health statistics collected by government. Although the model failed a simultaneous F-test, more descriptive investigation of its output suggested that this was correlated with actual attendance data.

Further refinement of this attendance model will now be made, so that it can eventually be combined with a model of the causes of poor nutrition. The household survey described here will be used to develop a model of under-nutrition prevalence in children under 5 years, which uses a rule-base to determine the nutritional status of all members of the household [Gundry et al, 1997]. Using the attendance simulation described here, such a model can then be tested against data for children measured at health centres. In addition, the same technique applied here can be used to identify areas where the probability of healthcare uptake is low so that suitable locations can be identified for potential new facilities.

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**IDENTIFYING TEMPORAL AND SPATIAL TRENDS IN GROWTH
MONITORING DATA AND THE LINKS TO SOCIO-ECONOMIC AND
ENVIRONMENTAL VARIABILITY IN ZIMBABWE.**

{short title : **TRENDS IN GROWTH MONITORING DATA**}

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Abstract:

This paper identifies patterns in child growth monitoring data and relates these to long-term socio-economic, environmental and physical characteristics of Zimbabwean districts. The data used are not based on small sample primary surveys, but rather are national data sets with broad spatial and temporal coverage. Data reduction techniques are applied to the interdependent set of potential causative variables to provide four compound determining factors. The relationship between these four factors and growth monitoring data, standardised to 1991, the mid-point of the times series, is then analysed using linear regression. Whilst the nutritional status of under-5s in Zimbabwe is shown to have improved, despite severe droughts, the HIV/AIDS epidemic and cutbacks in public expenditure, the proportion of underweight children is higher in areas where sanitation, water and housing facilities are below average. Districts with a better educated population and greater numbers of wealthy households also have lower percentages of underweight children. Use of secondary data in this way can provide an efficient method to identify the patterns and causes of wide area changes in nutritional data and so complement more localised field surveys.

Key Words:

Growth Monitoring, Nutritional Status, trends, Zimbabwe.

INTRODUCTION:

The increasing availability of spatially referenced, disaggregated data sets in a digital format provides an opportunity to investigate patterns in nutritional status at district level. These can complement more localised, household and community-level studies which cover smaller areas and are often cross-sectional. African nutritional monitoring systems are now quite widespread and at least five other sub-Saharan nations have clinic-based systems which use weight-for-age and are similar to the one described here (Quinn and Kennedy, 1994). Since many of these systems have been operating since the mid-1980s, there are now longer time series of information available. With the increasing use of computers for data collection and monitoring by governments in developing countries, the contribution of such secondary sources of information to our understanding of health-related problems is likely to increase.

This paper uses nutritional monitoring data for Zimbabwe to test some hypotheses about trends in under-nutrition between 1988 and 1995. It is argued that three new forces – drought, the HIV/AIDS epidemic, and the Economic and Structural Adjustment Programme – should have increased levels of under-nutrition during the latter half of this period. In addition, the paper relates long-term socio-economic and physical characteristics of Zimbabwean districts to patterns of persistent weight-for-age malnutrition identified through the growth monitoring data. Causes of poor nutritional status identified at household level can thus also be investigated at district level.

Zimbabwe's Growth Monitoring Programme:

A growth monitoring programme has been operating in Zimbabwe since 1987, with nutritional assessment based on weight-for-age in children under 5 years old. The programme was established by the Nutrition Unit in the Ministry of Health as part of the National Health Information System (NHIS) (Lenneiye, 1991). One of the stated goals of

the government of Zimbabwe is the alleviation of malnutrition and the programme is intended to monitor the extent to which this has been achieved. The system monitors children under 5 years, since this group is thought to be the most nutritionally vulnerable. Children are weighed at health centres or mobile field clinics, and those with weight-for-age below the third percentile of a standard population recognised by the World Health Organisation (WHO) are classified as underweight. Each health centre or mobile clinic records details of children weighed on a tally sheet and at the end of the month passes this on to the main hospital for the district. These tally sheets are then either computerised at the district hospital or transferred to a summary sheet manually and sent to Harare for computerisation.

Growth monitoring information was obtained from the Zimbabwean Ministry of Health for the periods from January 1988 to March 1993 and from January 1994 to December 1995. This information was available for 57 districts throughout Zimbabwe from the NHIS and was also broken down into four different age classes.

The potential sources of error in such clinic-based growth monitoring schemes have been described elsewhere (Ruel, 1995). Error can be introduced as a result of incorrect age assessment, miscalibrated scales, and recording, transcription and data entry errors. However, when considering trends in large populations over several years, most of these randomly occurring errors are unlikely to produce bias and so under- or over-estimate nutritional deficiencies. Of greater concern is the sample bias caused by the differences between those under-5s who participate in the formal healthcare system and those who do not. A survey by the Ministry of Health in 1991 of 35,000 children under-5 indicated that 89% possessed Child Health Cards (Government of Zimbabwe, 1992). Although this indicated that the use of formal healthcare was widespread, the frequency of weighings under the programme declined from an average of 7 in the first year of life to a situation where most children were not weighed in the third, fourth, and fifth years of life. Thus, the most likely source of bias in the regional growth monitoring data is through differences in the frequency of attendance, rather than because of the small minority who do not participate in the programme whatsoever. This frequency of attendance appears to vary, depending on the child's age, health status, and socio-economic characteristics. However, despite these differences in frequency of attendance, the clinic-based assessment of the prevalence of underweight at national level from the NHIS is consistent with a community-

based national survey carried out in 1988. This survey, the Demographic and Health Survey (DHS), found almost the same national prevalence of underweight as the NHIS for 1988 (UN ACC-SCN, 1992), but was free from the bias associated with monitoring at clinics. This suggests that 'the surveillance data are reliable at national level'¹ (ibid., p. 5).

Changes in Causes of Under-Nutrition in Zimbabwe:

Over the period under study, three threats to further improvements in child nutritional status have emerged. Firstly, the HIV/AIDS epidemic in Zimbabwe has clear implications for child nutrition. HIV prevalence is difficult to estimate, but figures based on sero-prevalence in pregnant women have suggested prevalence of 25% in this group (McCarty 1994; Tagwireyi & Greiner, 1994) and local prevalence as high as 30% (Gregson, 1995). Zanamwe et al (1994) have suggested that the Zimbabwean HIV-positive population will increase from 800,000 as recorded at the end of 1992 to 3.75 million by the year 2000. Vertical transmission of HIV from mother to child is exposing an ever-growing number of young children to disease and consequent weight loss. As the number of orphan children grows, traditional means of caring for orphaned children are likely to come under increasing pressure. Zanamwe et al (1994) have suggested that 'much of the burden of orphan-caring may well fall on the elderly' and this too may adversely affect their nutritional status.

Secondly, in 1991-92 Zimbabwe suffered a drought which was 'the worst in living memory' (Scoones 1996: p 164), with mean annual rainfall only 24% of normal in parts of the communal lands, communal area grain production negligible, and national strategic grain reserves exhausted. A massive relief operation began, with the first food aid arriving in the country in April 1992, and 4-5 million people receiving aid at the height of the drought (Scoones 1996: p. 175). The drought is likely to have affected not only access to food during 1992, but also to have reduced the asset base of much of Zimbabwe's rural population. In Chivi district, only 34% of bulls and oxen survived the drought and the number of households who did not own any cattle rose from 55% to 68% (Scoones, 1996: pp 206-208). The effect of such erosion of assets is likely to have lasted well beyond the period of food shortage, with the loss of draught power being one result of such high cattle mortality. The nutritional impact of the drought should also be apparent in the growth

¹ The NHIS found 11.4% of attendees to be below the 3rd percentile, whilst the DHS found 11.5% of

monitoring data for some time after the event, given that the weight-for-age measure should reflect stunting (chronic malnutrition) as well as wasting.

Thirdly, since 1991 the Government of Zimbabwe has adopted an Economic and Structural Adjustment Programme (ESAP) under pressure from the World Bank and donor community (Moyo, 1995). The main thrust of ESAP has been to liberalise markets and to reduce public expenditure. The effects of the drive to reduce public expenditure are likely to have adversely affected the general well-being of the population of Zimbabwe (at least in the short-term). The policy was associated with widespread retrenchments (job losses) and cut-backs in expenditure on healthcare and public welfare. In 1995, for example, the government's food aid programme was replaced by a grain loan scheme that required repayment of food relief following the next adequate harvest. All of these factors would suggest that an increase in the prevalence of child weight-for-age malnutrition is likely, especially in the second half of the study period.

Socio-Economic and Environmental Factors Affecting Under-Nutrition :

Table I shows a set of socio-economic and physical variables that were postulated to affect aggregate nutritional status at district level. These variables were selected because they reflected one or more of the three principal influences on children's nutritional status proposed by Tagwireyi and Greiner (1994): household food security, health environment and services, and care for children. The variables selected are intended to represent persistent causes of poor nutritional status which change slowly over time and are likely to have affected the under-5 population throughout the period under study. Socio-economic variables were largely derived from the August 1992 census (Government of Zimbabwe, 1993), which took place close to the mid-point of the period under study. Two variables (access to safe water and access to adequate sanitation) were selected for their impact on health status. Distance to water source was included separately because of its impact on the time spent fetching water by rural women, which reduces the time available for child care, other household chores, and income generation (Burger and Esrey, 1995). Rukuni and Jayne (1995, pp. 9-10) suggest that Zimbabwean mothers with no formal education are two to three times more likely to have stunted or wasted children than those who have received

under-5s to be below the 2.3 percentile.

secondary level education or higher. The proportion of illiterate females aged 15 years or over was also included as an indicator of adequate child care, albeit that it may also reflect poverty.

Table I: Socio-economic and physical variables affecting percentage of underweight children under 5 years for Zimbabwean districts.

Measure	proxy for:	source
Proportion of households in traditional housing	extent of poor, rural households	census
Proportion of households in mixed housing	extent of wealthy, rural households	census
proportion of households in modern housing	extent of wealthy households	census
percentage of urban population	extent of urban households	census
proportion of households without safe water (i.e. using rivers/unprotected wells)	exposure to disease as a result of infra-structure	census
proportion of households with water source >1 km away	time available for childcare and income generation	census
proportion of households without any sanitation facility	exposure to disease as a result of infra-structure	census
sex ratio in people over 15	proportion of female-headed households & reliance on remittance income	Census
mean annual precipitation	basic constraints on agricultural production	CRES topographic & climatic database for Africa
proportion of area under commercial farming	nutritionally vulnerable commercial farm workers	Land Use Map
Density of road network	infra-structural development	Digital Chart of the World
proportion of women over 15 years illiterate	Childcare and weaning practices.	Census

Six other variables were considered to affect nutritional status through all three of the routes listed above, and also enabled the identification of major socio-economic groups within the population. The proportion of urban households in each district was selected because urbanisation profoundly alters livelihoods, changing diet and channels used to obtain food. The concentration of hospital and doctors in cities also means that healthcare availability is better than in rural areas (Chimhowu and Tevena, 1991). In the rural sector, information on type of housing provides an indication both of wealth and market involvement: modern housing is restricted to the rural elite and the urban population, 'mixed' housing (for instance, traditional dagga walls combined with tin roofs) suggests the presence of a wealthier rural group and poorer urban areas, whilst 'traditional' housing is associated with the rural poor. Another important subset of Zimbabwe's rural population are the workers in the Large Scale Commercial Farming (LSCF) sector, formerly known as the European Areas under colonial rule and Ian Smith's Unilateral Declaration of Independence (UDI). The extent of this group was represented by the proportion of land under the LSCF sector, which was calculated by overlaying a district boundary map on land use boundaries within a geographical information system (GIS). Food access for this group tends to be through market purchases, rather than through subsistence production. Amanor-Wilks (1995) has argued that the commercial farming workforce are among the most nutritionally vulnerable in Zimbabwe today, having benefited much less from post-independence improvements in education and healthcare than the Communal Areas. In addition, the widespread employment of labourers on a seasonal contract basis makes commercial farm workers' wages and food purchasing ability dependent on an unreliable source of income (Rukuni and Jayne, 1995: p. 11). The Communal Areas consist of lower potential land set aside for the indigenous population during the colonial period and tend to act as reserves of labour both for the cities and the LSCF. As a result, many communal households are dependent on remittance income from absentee adult males, whilst women are responsible for agricultural work and child care. Following Zanamwe's (1991) study of district age-sex structure, adult sex ratio was used as an indicator of these areas of male out-migration.

Finally, two further variables were included which were related to the physical characteristics of each district. Mean annual rainfall for each district was used as a measure of one of the basic constraints on agricultural production. This was calculated using a GIS by overlaying district boundaries on a mean annual rainfall image for the period 1920 to

1980 derived by Hutchinson et al (forthcoming). As a measure of infra-structural development within each district, the density of the road network was similarly calculated by overlaying district boundaries on a digital road map taken from the Digital Chart of the World (ESRI, 1991).

METHOD:

Several consistency checks were performed on the growth monitoring data prior to analysis. Firstly, a check was made to ensure that the number of children weighed was always greater than the number recorded malnourished for all age groups. Secondly, in cases where identical figures had been entered onto the database for a district for two or more consecutive months, these were omitted from the analysis. Given the scope for data entry, transcription, or aggregation errors in the system described above, extreme values were also flagged and excluded from subsequent analysis. Such values were identified by calculating the inter-quartile range for each district and finding values which lay more than 3 inter-quartile ranges above or below the median. This flagging procedure was used both on the numbers of children who were weighed and on the percentage of children underweight and is adapted from Haining (1990: p. 200). 1% of the total number of monthly data points were flagged using this procedure. Figure 1 shows data values flagged using this method for Gweru District. Finally, the number of children weighed and the percentage of underweight children were examined as time series graphs to identify changes in growth monitoring administration procedures.

Over the period covered by the data (1988-1995), several Zimbabwean districts underwent boundary changes. These problems were solved by amalgamating growth monitoring data for neighbouring districts where boundaries had changed. Umguza district, for which growth monitoring information was only available for 1994-95, was excluded from the analysis described below (see Map 1 for locations of places referred to in the text).

To characterise the nutritional situation in different parts of the country, a linear regression was performed for each district of time against percentage weight-for-age malnutrition. For this regression, time was measured in months and standardised so that the

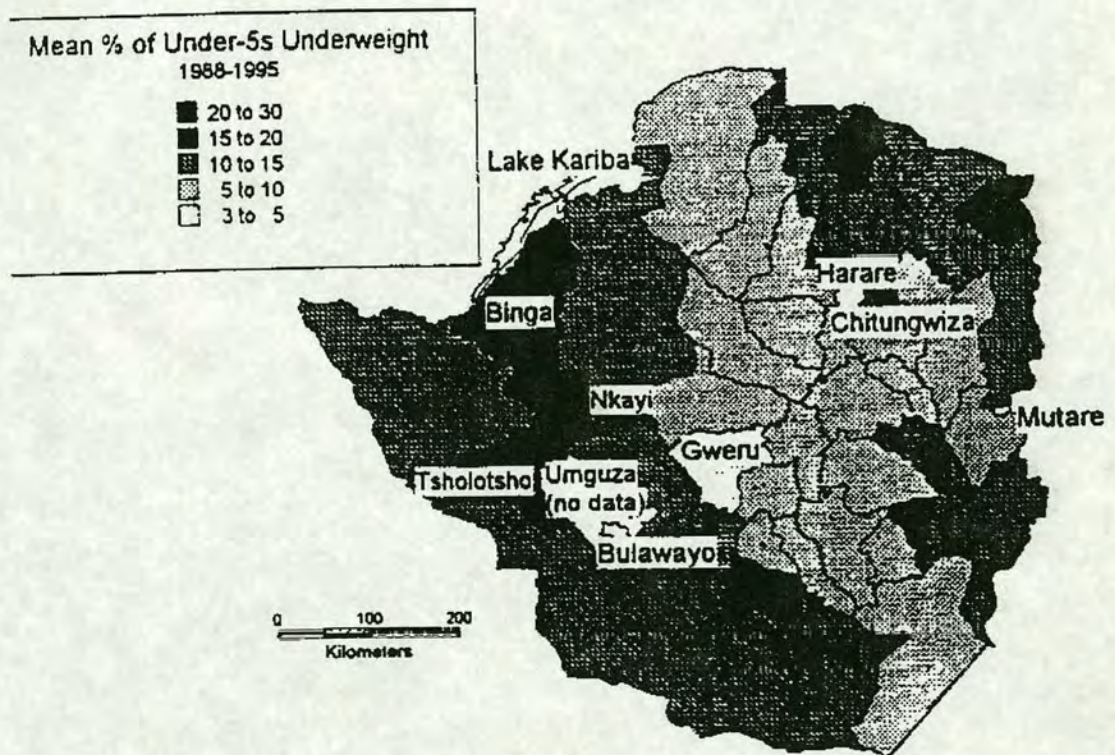
mid-point of the monitoring period (the end of 1991) was zero. This meant that the intercept term of the regression equation for each district was an estimate of the mean malnutrition rate for the period. Given that the number of months of available data varied between districts, this provided a more comparable measure of average nutritional conditions than the arithmetic mean of the monthly rates. Furthermore, the slope of the regression line represented the time trend in the percentage of children underweight. By way of illustration, Figure 1 shows the change in the percentage of underweight over time for Gweru District. The fitted regression line against time is also shown, together with extreme values identified during initial data exploration and excluded from the analysis. The intercept of 3.9% represents the estimated mean prevalence of child malnutrition in the district for the period 1988 to 1995.

Relating such a large number of socio-economic and physical variables to nutritional status was likely to be difficult, and so the variables were summarised first to simplify this process. The variables were submitted to a data reduction technique known as factor analysis, which reduced them to a smaller number of new variables, called *factors*. These factors contain most of the information in the original variables and are uncorrelated with one another. However, each new factor does not correspond directly to any one of the original variables, but rather contains information from several different variables. The small number and absence of correlation between the resultant factors makes them suitable for subsequent regression analysis, although their composite nature makes interpretation of results more difficult than methods which use the original variables directly.

The relationship between the physical and socio-economic district characteristics and the estimated mean percentage underweight was investigated using linear regression. The factors from the factor analysis representing physical and socio-economic conditions were regressed against the estimated mean percentage of underweight children within each district. This tested the strength of the relationship between mean percentage underweight and the districts' physical and socio-economic characteristics.

RESULTS:

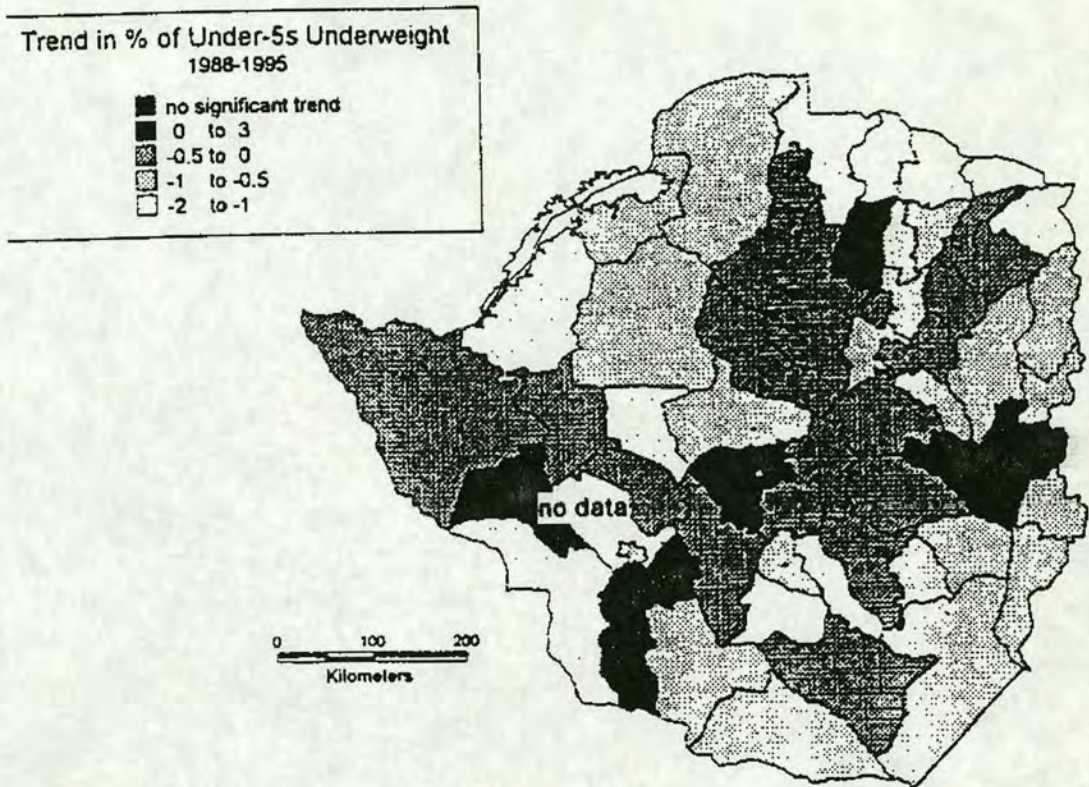
Map 1 shows the estimated mean percentage of underweight children during the period 1988-95. Several geographical patterns can be discerned, notably that urban areas (Bulawayo, Mutare City, Harare, and Chitungwiza) show lower rates of weight-for-age malnutrition than rural areas. The proportion of underweight children in these areas is close to the 3% figure which would be expected in the WHO standard population. Secondly, the situation in Binga District on the shores of Lake Kariba is considerably worse than anywhere else in Zimbabwe. Thirdly, the more arid parts of the country in Matabeleland, the Zambezi valley, and northern Mashonaland show higher weight-for-age malnutrition than the highveldt areas in the centre of the country.



Map 1: Mean percentage of underweight children under 5 years by district, 1988-1995.

Map 2 shows the estimated time trend in the percentage of children underweight. In 49 districts out of a total of 57, the trend in underweight over the period 1988-95 was downwards; in 6 districts there appeared to be no significant trend; and weight-for-age

malnutrition had increased in only 2 districts, both of which showed very low percentages of under-weight children at the start of the time series in any case.



Map 2: Trends in percentage of underweight children under 5 years by district, 1988 - 1995.

Figure 2 shows the estimated trend in weight-for-age undernutrition plotted against the estimated mean percentage of underweight children. This shows that the reduction in the proportion of underweight children is lower in districts where the mean level of child malnutrition is low. Again, the percentage of underweight in Binga District lies well above the national average, though the situation there has been improving by 1.8% per year over the study period. In addition, however, two districts of rural Matabeleland (Tsholotsho, and Nkayi Districts) show high levels of weight-for-age malnutrition, which have not been reduced significantly over the study period.

The factor analysis reduced the original data set to four factors, which accounted for 80.9% of the variation in the original variables. Table II shows the proportion of the total variation in all of the original variables accounted for by each of the four factors identified. The first two factors created contain most of the information in the original data set.

Table II: Percentage of variance explained by factors from factor analysis.

Factor	% of total variance explained	Cumulative % of total variance explained
1	44.1	44.1
2	16.4	60.5
3	10.5	71.0
4	9.9	80.9

Table III shows the strength of the relationship between the four factors created by the factor analysis and the original variables. These extracted factors can be broadly characterised as follows:

- The first factor was strongly related to the proportion of households in traditional housing, the proportion of households with unsafe sanitation, the proportion of households more than 1km from a water source, the proportion of households with unsafe water sources and inversely correlated with the proportion of urban households and households in modern housing. This factor appeared to represent rural living conditions.
- The second factor was primarily related to mixed housing and to a lesser extent with mean annual rainfall. This factor appeared to represent the extent of a wealthier rural group, able to afford more expensive housing materials.
- The third factor was related to road density, though somewhat weakly.
- The fourth factor was positively associated with male: female ratio and negatively with the proportion of land area under commercial farming. This appeared to represent those communal areas which are a source of labour for the LSCF and urban areas.

The communality figures in Table III indicate the extent to which all four factors combined represented the information in each of the original variables. Thus, sex ratio, road density, and mean annual rainfall were the three variables most poorly represented by the final set of factors, whilst the proportion of urban population was well represented.

Table III: Factor loadings for socio-economic and infra-structural variables from the factor analysis (Figures in bold indicate the strongest factor loadings for each variable).

Variable	Communality	Factor 1	Factor 2	Factor 3	Factor 4
% of LSCF land	.81	-.22	.45	.38	-.65
% of illiterate women over 15 years	.83	.70	-.24	-.45	-.27
mean annual rainfall	.73	-.23	.60	-.54	.18
male: female ratio	.48	-.19	.04	.10	.65
% of households in 'mixed' housing	.88	.19	.90	.21	.06
% of households in 'non-traditional' housing	.97	-.95	-.26	-.09	.01
Road density	.64	-.36	-.10	.66	.24
% of urban households	.93	-.88	-.33	-.17	.13
% of households in 'traditional' housing	.94	.95	-.17	-.01	-.04
% of households using unsafe sanitation	.87	.89	-.16	.12	.20
% of households with water sources >1km away	.83	.77	-.40	.28	.02
% of households using unprotected water sources	.81	.73	.39	-.06	.35

Table IV shows the results of the linear regression of the four factors against the estimated mean malnutrition for each district during 1988-1995. Factors 1 and 2 were found to be significantly related to the estimated mean underweight prevalence for the 57 districts.

Table IV: Results of linear regression of factors extracted from the factor analysis on mean malnutrition rate for 57 districts (= significant at the 99.9% level; * = significant at the 99% level; n.s. = not significant. The R^2 value for the fitted equation was 0.63 and the F-Statistic for the regression was significant at the 99.9% level.)**

Coefficient	Significance of T
Factor 1	**
Factor 2	*
Factor 3	n.s.
Factor 4	n.s.
(Constant)	**

DISCUSSION :

The overall reduction in weight-for-age malnutrition is somewhat surprising given that three new forces could have adversely affected child nutrition during this period. One possible explanation as to why these three factors do not appear to have exacerbated weight-for-age malnutrition during the study period is the Zimbabwean government's commitment to improving rural living conditions. The post-independence period witnessed increased expenditure in rural development and health (Government of Zimbabwe, 1990). The benefits of several of the measures adopted - which included the establishment of a primary healthcare service, nutritional education programmes, investment in sanitation and water facilities, and the introduction of a child supplementary feeding programme - may still be reducing the prevalence of underweight in under-5s, even though most were introduced prior to the period under study. Major government and NGO relief operations during the 1991-92 drought also undoubtedly mitigated its immediate impact (Thompson, 1993).

The reduction in underweight prevalence may also reflect the ability of apparently vulnerable households to cope during times of hardship. During the 1991/92 drought, for example, communal households used a wide range of coping strategies to sustain themselves - including working off-farm, pottery-making, selling vegetables, beer, or livestock, and gold-panning (Scoones, 1996). There is, of course, no guarantee that such strategies will continue to be successful in the future under conditions of prolonged stress.

The effects of structural adjustment on levels of under-nutrition may also have varied across the country. Public sector job losses associated with expenditure cutbacks were concentrated in urban areas, and this may in part explain the absence of any nutritional improvements in the cities. Whilst the effect of public expenditure reduction is likely to have adversely affected nutritional status, the effect of internal market reforms appears more complex. Although some have argued that the removal of price controls designed to protect lower income groups can only be detrimental to the poor (Kadenge, 1992), the effect of market liberalisation on nutritional status may not be quite so straightforward. It is known that the tightly controlled maize marketing policies of the 1980s channelled grain surpluses into cities, inhibited rural grain processing capacity, and encouraged distribution and consumption of highly refined, less nutritious, commercial maize meal (Jayne and Chisvo, 1991). In addition, recent work has shown that one consequence of liberalisation has been greater movement of grain from surplus to deficit rural areas (Vaze et al, 1996).

Another somewhat unlikely possibility is that the growth monitoring data do not adequately represent the trend in weight-for-age in the Zimbabwean under-5 population as a whole. This would imply that the degree of bias in the subset of children who participate in the programme has changed over time. Whilst it is not feasible to test against this possibility post-1988 in retrospect, periodic community-based anthropometric surveys such as the DHS would provide a means of testing for this eventuality, provided they used the same anthropometric standards as the NHIS.

The high prevalence of weight-for-age malnutrition in Binga District can be explained by the living conditions within the district. The socio-economy of this district has been examined in detail by Muir (1993) who found that opportunities for income generation or agriculture were limited and that the Tonga people in the district were heavily reliant on food aid for a living. The factor analysis showed that the proportion of households lacking adequate sanitation and water supplies, living in traditional housing, and the proportion of illiterate women were related to urbanisation. The significant relationship identified by the linear regression between the first factor, which appears to represent the proportion of rural population, and the mean percentage of underweight children is therefore unsurprising. This is consistent with the 1988 DHS survey which found 'substantially more stunting in the rural areas, but not much wasting in either urban or rural areas' (ACC-SCN, 1992: p. 10). The second extracted factor, which was strongly related to the proportion of households

living in 'mixed' housing was inversely related to mean percentage weight-for-age malnutrition. This is consistent with the suggestion made earlier that such 'mixed' housing was indicative of the presence of a wealthier rural group who are less vulnerable to the causes of malnutrition than the poor.

The apparent persistence of a high proportion of underweight children in parts of rural Matabeleland is consistent with findings presented by Rukuni and Jayne (1995: p. 7), based on a province-level analysis of data on stunting. They attributed the lack of an improvement in stunting in Matabeleland to the particular severe succession of droughts experienced in the area in the late 1980s. However, this does not explain the persistence of a high proportion of underweight children throughout the 1990s.

CONCLUSION:

Underweight children under 5 are more prevalent in rural areas of Zimbabwe than urban areas and where there is evidence that the wealthier rural class is smaller. This reflects the distribution of poor sanitation, educational, housing, and water resources. The continued improvement in the nutritional status of under-5s between 1988 and 1995 runs against the expected trend, given the effects of drought, structural adjustment and HIV/AIDS. This improvement in nutritional status may reflect the effects of government commitment to improving rural living conditions, but may also indicate that the Zimbabwean population has so far successfully coped with adverse conditions. A reduction in poor nutritional status does not appear to have been experienced by children everywhere, however, and the persistence of a high percentage of underweight in rural Matabeleland merits further investigation. Although the trend towards lower child malnutrition in Zimbabwe has already been well documented (Tagwireyi and Greiner, 1994: pp 1-2), the assessment of these trends in relation to district characteristics represents a more innovative use of secondary data about nutrition.

Further research is underway which looks at the relationship between short-term changes in agricultural, socio-economic, meteorological, and health indicators and growth monitoring data and at more local patterns in nutritional status.

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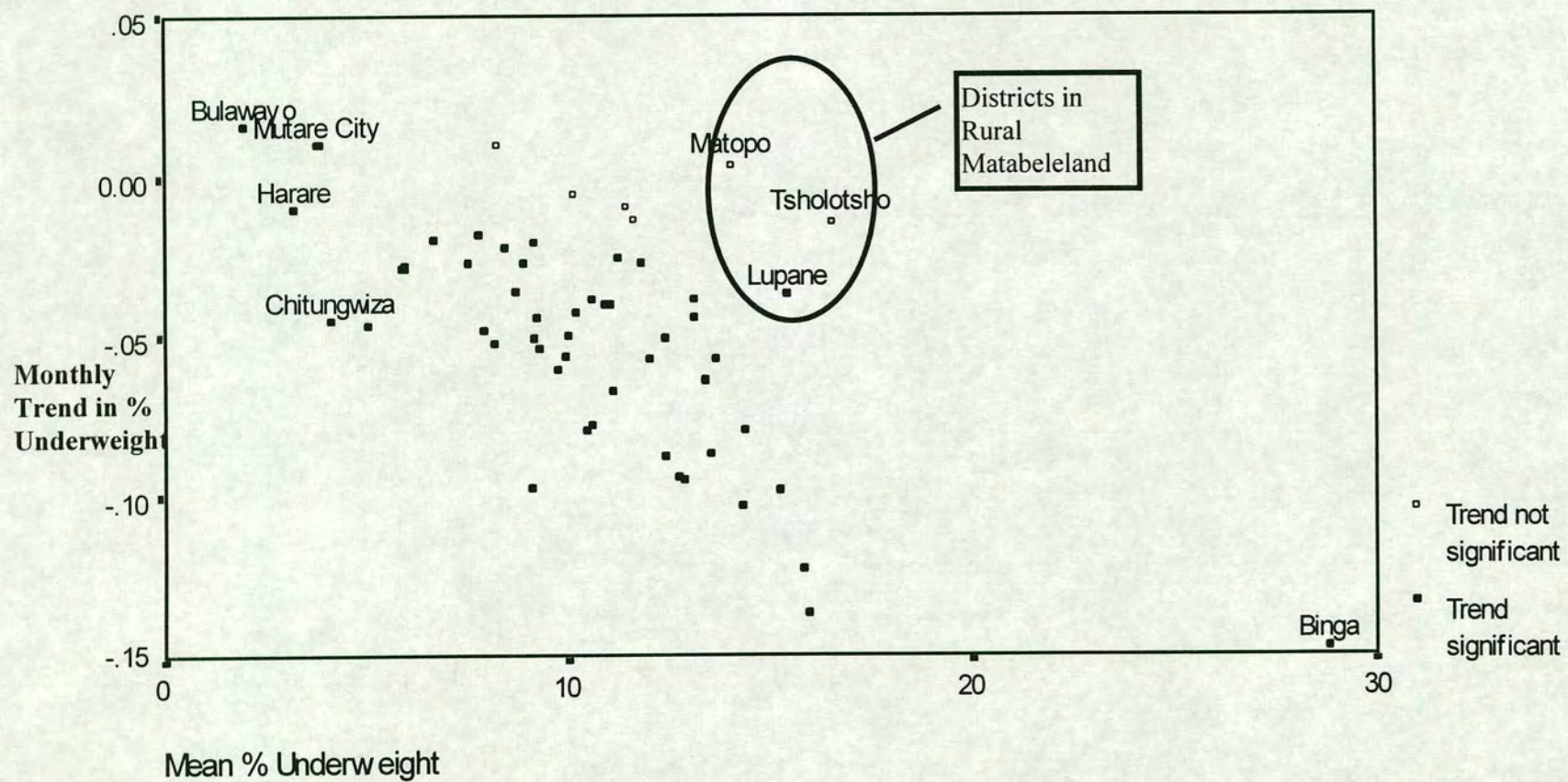


Figure 1: Example of fitted regression line for Gweru District.

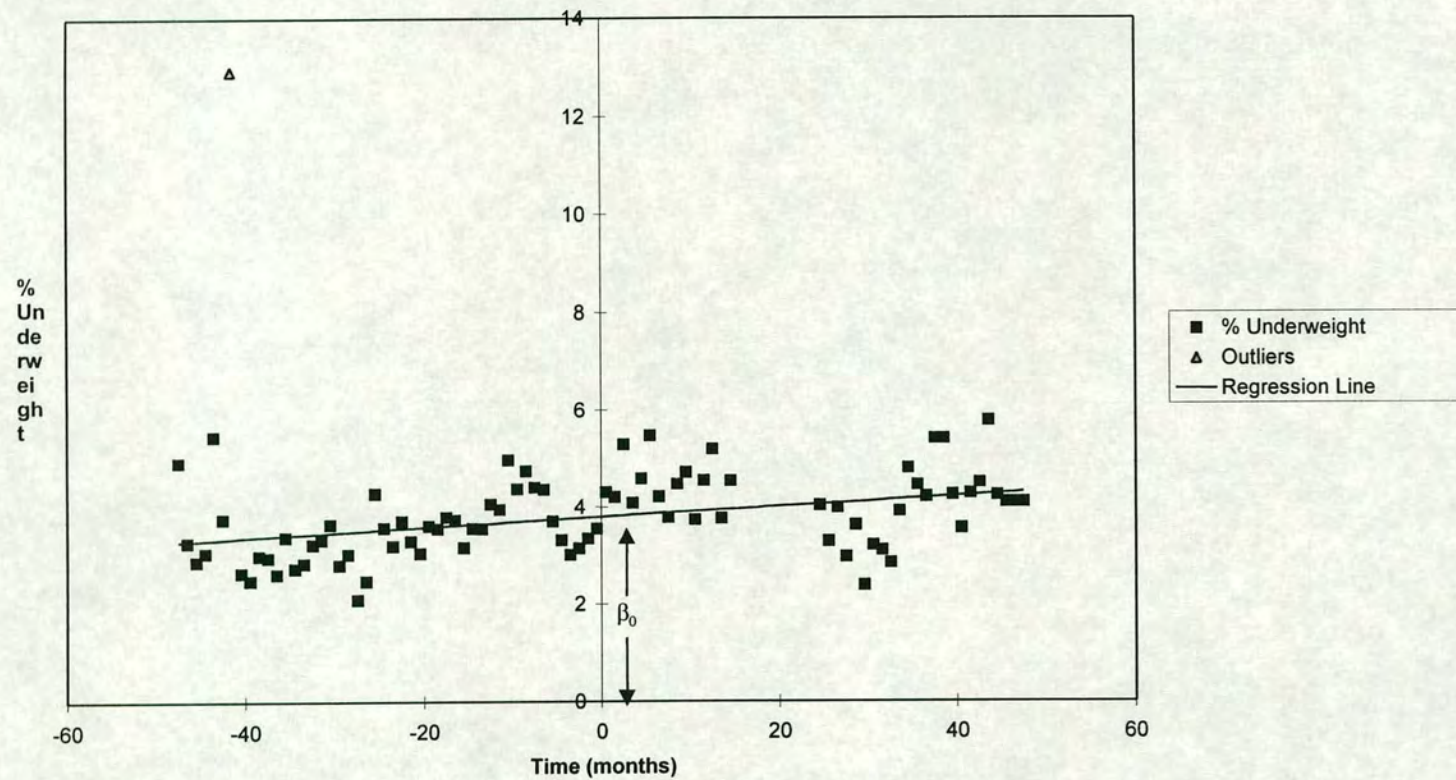


Figure 2: Mean trend and percentage of underweight children under 5 years by district, 1988-1995.